BANK OF CANADA
BANQUE DU CANADA

Staff Working Paper/Document de travail du personnel—2024-51

Last updated: December 19, 2024

Bouncing Back: How Mothballing Curbs Prices

by Thibaut Duprey,[1] Artur Kotlicki,[2] Daniel E. Rigobon[3] and Philip Schnattinger[4]

[1] Financial Stability Department
Bank of Canada
tduprey@bankofcanada.ca

[2] Bank of England
artur.kotlicki@bankofengland.co.uk

[3] Princeton University
drigobon@princeton.edu

[4] Bank of England
philip.schnattinger@bankofengland.co.uk

DOI: https://doi.org/10.34989/swp-2024-51 | **ISSN** 1701-9397

Acknowledgements

We would like to thank Kenan Fikri, Matheus Grasselli, Erica Groshen, André Kurmann, Soyoung Lee, Danny Leung, Alberto Polo, Ricardo Reis, Nicholas Sander and Tim Willems for their comments at various stages of this project. We benefited from helpful comments by participants at our presentations at the American Economic Association’s Allied Social Science Associations 2023 Annual Meeting, the European Economic Association–Econometric Society European Meeting 2024 and at the Bank of England and Bank of Canada. The views expressed in this paper are those of the authors and do not represent those of the Bank of Canada nor of the Bank of England or their committees.

Abstract

We investigate the macroeconomic impacts of mothballed businesses—those that closed temporarily—on sectoral equilibrium prices after a negative demand shock. First, we introduce a new establishment-level dataset derived from Google Places. We confirm the importance of temporary closures during the COVID-19 pandemic. Data on establishment reviews also suggests that preventing productive businesses from permanently exiting could support employment. Second, we embed these findings into a model of heterogeneous firm dynamics. By maintaining productive capacity during downturns, temporary closures initially support employment and subsequently reduce price pressures. Our results suggest that pandemic fiscal support for temporary closures may have eased inflationary pressures.

Topics: Central bank research; Firm dynamics; Fiscal policy; Inflation and prices
JEL codes: D22, E32, C55, C81

Résumé

Nous étudions l'incidence macroéconomique des entreprises dont les activités ont été mises en veilleuse – c'est-à-dire des entreprises qui ont été fermées temporairement – sur les prix d'équilibre sectoriels après un choc de demande négatif. En premier lieu, nous nous fondons sur un nouveau jeu de données lié aux établissements provenant de Google Places. Nous confirmons ainsi l'importance du rôle des fermetures temporaires durant la pandémie de COVID-19. L'examen des données sur les avis des établissements donne aussi à penser que le fait d'éviter la fermeture définitive d'entreprises productives aurait pour effet de soutenir l'emploi. En second lieu, nous intégrons ces résultats dans un modèle dynamique comportant des entreprises hétérogènes. En maintenant la capacité de production en période de ralentissement, les fermetures temporaires soutiennent tout d'abord l'emploi et atténuent ensuite les pressions exercées sur les prix. Nos résultats indiquent que les mesures budgétaires ayant permis des fermetures temporaires pendant la pandémie pourraient donc avoir allégé les pressions inflationnistes.

Sujets : Recherches menées par les banques centrales; Dynamique des entreprises; Politique budgétaire; Inflation et prix
Codes JEL : D22, E32, C55, C81

1 Introduction

Large aggregate demand shocks often lead affected businesses to shut down their production. Whether these businesses decide to shut down production today but plan to reopen tomorrow is challenging for policymakers tasked with assessing the current supply capacity of the economy. The COVID-19 pandemic is an example of a severe aggregate demand shock, especially in consumer-facing sectors. In these sectors, the pandemic led to the temporary closures of many businesses that *mothballed* their way out of the most stringent restrictions, partly supported by extraordinary government measures. As the economy progressively re-opened, fiscal support and supply bottlenecks contributed to large inflationary pressures not experienced for decades. In this paper, we explore the link between temporary business closures and equilibrium prices in sectors after an aggregate shock.

We highlight a new channel whereby mothballing businesses during an aggregate shock can curb pressures on equilibrium prices by sustaining immediately available supply when the economy is subsequently bouncing back. First, we estimate the prevalence of temporary business closures, using a novel method that leverages the data behind the Google Maps service. We then introduce a mechanism for temporary closures into an otherwise standard model of business dynamics. The model presents a new channel through which temporary closures, following an aggregate exogenous demand shock, initially support employment and then increase equilibrium supply and reduce price increases during the reopening phase, that is, when the demand shock subsides.

Our contribution is two-fold. While the mothballing of businesses has been studied by economists at least since Dixit et al. (1994), we build a new method for the identification of temporary business closures using Google Places data, the database behind the Google Maps service. By comparing the appearance and disappearance of business establishments on a map between two time points and using the associated metadata, we can distinguish businesses temporarily closing and subsequently re-entering from those exiting permanently as well as the entry of new businesses. We apply this method to the food-service and retail sectors of major Canadian cities during the COVID-19 pandemic and derive several stylized facts.[1] First, temporary closures substantially contributed to the increase in business entry rates during the reopening phase of the pandemic. Second, we document a relationship between the number of customer reviews received by a business and both (i) the likelihood of a business remaining operational, and (ii) increased job vacancies, implying that review activity may be a proxy for business activity. This suggests that preventing businesses with good reviews from permanently exiting during the pandemic could have supported productivity and employment. Third, we observe a correlation across Canadian provinces between higher temporary closures during the pandemic and lower subsequent consumer prices.

We capture these observations by extending a standard firm dynamics model (Hopenhayn, 1992; Hopenhayn and Rogerson, 1993) to allow for temporary business closures. At the beginning of each period, firms observe their realised productivity and decide whether to temporarily close their operations—saving a share of the fixed cost—or to continue operating. The model is calibrated to match the drop in business demand and the share of temporary closures in the food-service and retail sectors during the pandemic in Canada. Through the lens of our model, we identify a new channel whereby temporary closures after an aggregate demand shock dampen the pressure on the equilibrium price. Under our calibration, had temporary closures not been possible during the pandemic, pressures to increase prices due to reduced supply in the food-service (brick-and-mortar retail) sector would have been 26 (18) basis points larger in 2022 and 2023 after the lifting of COVID-19 restrictions. Our model is crucial to identifying this channel, given that we do not observe establishment-level price changes in the Google Places dataset. The rationale for our mechanism is as follows. During the pandemic, temporary closures supported survival rates for borderline productive firms,

[1] In Canada, the food-service sector accounts for around 6% of final consumption spending and 7% of employment. The brick-and-mortar retail sector accounts for around 5% of final consumption spending and 12 % of employment.

leading to both (i) higher supply capacity during the reopening phase and (ii) mothballed firms experiencing lower reopening costs relative to new firm entries. In contrast, higher fixed costs for new entrants, costly new entries taking up resources (Bilbiie et al., 2012), and limited supply would have put more pressure on employment and prices, leading to higher fixed and wage costs and ultimately higher prices.

This research underscores the pivotal role of temporary closures in bolstering economic resilience, sustaining supply, and limiting inflationary pressures, particularly in the face of business dynamics disrupted by aggregate but temporary demand shocks. The results point to a channel whereby government spending targeted to support temporarily closed businesses can generate *downward* pressure on inflation during a recovery, in contrast with the broader view that untargeted government support may create *upward* pressure on inflation. The indicative negative correlation between temporary closures and inflation during the pandemic can be explained, through the lens of our model, by a higher supply capacity upon re-opening that lowers the pressure on sectoral prices as the economy returns to the long-run equilibrium. That said, this paper's parsimonious model of business dynamics does not aim to explain post-pandemic inflation as it does not include many other quantitatively relevant channels.

This work contributes to three strands of the literature. First, we contribute to the literature on the timely measurement of business dynamics and temporary closures. Official statistics are released with a time lag, but the speed of the pandemic highlighted the need for non-traditional real-time statistics on business health. Crane et al. (2022) provides an overview of some non-traditional datasets that can be used to measure business entry and exit dynamics, such as Google searches, paycheck issuance, and phone-tracking data from providers like SafeGraph Places. They find that at least some of these measures can capture the main trends well. For instance, Yelp (2020) used its platform's business reviews by customers to compute the relative importance of temporary and permanent closures during the early phase of the COVID-19 crisis. Statistics Canada (2021) further merged business openings and closures from Google Places with foot-traffic data from Google to create an index of business activity. Experimental estimates of business openings and closures built during the pandemic are now available monthly with a three-month lag in Canada (Statistics Canada, 2020) or quarterly with a one-month lag in the United Kingdom (Office for National Statistics, 2022), compared to previous official statistics that lagged by one year. For the United States, monthly statistics on business applications are now available within a few weeks (Haltiwanger, 2021). Following our companion proof of concept (Duprey et al., 2022) that focused only on the food-service sector in Ottawa over four months, we provide new insights using Google Places as a timely measure of temporary closures over two years across a range of cities and sectors.

Second, we also contribute to the literature on the macroeconomic relevance of business dynamics during the pandemic. Business entry and exit dynamics are key determinants of long-run productivity (Hamano and Zanetti, 2017; Aghion et al., 2019) and employment (Sedláček, 2020). Using a U.S. sample, Kurmann et al. (2021) find that small businesses that reopened after the pandemic were key drivers of employment dynamics. Gourinchas et al. (2021) highlight that the risk of generous pandemic support policies turning non-productive firms into zombies is not as high as the risk of delayed failure rates for small- and medium-sized enterprises due to a contraction of corporate credit. Still, absent government support, financial frictions during a liquidity shock, like the pandemic, lead to inefficient business exits (Gourinchas et al., 2023). We find that government support aimed at reducing the cost of temporary closures may have helped to support employment and limit inflation through our proposed channel. The heterogeneous agent literature that models a distribution of firms explored the link between firm indebtedness and firm dynamics, but without focusing on temporary closures. For instance, in a model calibrated to the 2008 financial crisis, Bustamante (2020) shows that larger firm leverage increases the likelihood of experiencing a debt overhang problem that slows down recovery and leads to low inflation. Similarly, Khan and Lee (2023) find that a recession that coincides with a rise in leverage leads to fewer producers operating at efficient levels. By contrast, our model abstracts from the role of corporate indebtedness and we instead add the option to temporarily close, in a standard Hopenhayn (1992) model of firm heterogeneity.

Third, we contribute to the thin literature that directly models mothballing businesses. A firm's optimal option decision to remain idle at certain productivity levels when faced with adverse shocks has been studied theoretically in Dixit (1989) and Dixit et al. (1994). Since then, temporary shutdowns of production have been studied in quantitative models but has been rarely applied directly to the data. Guerra et al. (2018) theoretically study the conditions under which firms decide to mothball given a price path and find these decisions increase when the expectation of the price path is improving and more uncertain (both also apply to the period we study). Hamano and Zanetti (2017) and Hamano and Zanetti (2022) study firms with the option to remain idle or to produce in a tractable real business cycle model and a monetary model, but their focus is on the productivity effects rather than capacity and the equilibrium price. Buera et al. (2015) and Buera et al. (2021) study the quantitative effects of heterogeneous firms that draw a mandated temporary exit shock from production. We endogenise this firm decision to temporarily shut down.

The remainder of the paper is structured as follows. Section 2 introduces the new method used to quantify temporary closures using the data behind the Google Maps platform. Section 3 presents two new stylized facts around temporary closures for our sample of Canadian food-service and retail businesses. Section 4 embeds those observations into a standard model of business dynamics extended with temporary closures. Section 5 discusses the model simulation results on post-pandemic equilibrium price increases, and Section 6 concludes.

2 New data on business dynamics

2.1 Data

We use Google Places, the database behind Google Maps, to identify unique businesses in a desired geographic area. Although Google Places is likely to have comprehensive and timely data, the quality of our estimates depends on the underlying quality of the Google Places data, which is beyond our control. The information in business listings is compiled by Google from different sources:[2] business owners who have a business account, customers who provide reviews, users who report inaccurate listings, or other publicly available information (e.g., an official website).

For several reasons, we focus on the retail, accommodation, and food-service sectors for the downtown core of the following cities: Ottawa/Gatineau, Montreal, Toronto, and Vancouver.[3] First, it is most likely that businesses in sectors with face-to-face consumer interactions would have timely and accurate reporting because those businesses have the strongest incentive to maintain their online presence on Google Maps. Second, areas with the most foot traffic are likely to have better data quality, due to reviews and reporting by Google users. Third, these sectors were the most affected by the COVID-19 crisis and, thus, the most relevant to track in a timely manner.

We use the functionality of "Nearby Search" in our queries to Google Places API,[4] which, instead of searching for a specific business, returns all businesses of a given type within a bounding circle, defined by a point (in latitude and longitude) and a radius (in meters).

[2] Refer to Google's local listings help for more details.

[3] Specifically, we focus on the following forward sortation areas (FSA) identified by the first three characters of their postal codes: K1A, K1N, K1P, K1R, K1S, K2P, J8X for downtown Ottawa/Gatineau; H2J, H2L, H2T, H2V, H2X, H2Y, H2Z, H3A, H3B, H3C, H3G, H3H, H3J, H3S, H3T, H3V, H3W for downtown Montreal; M4K, M4M, M4W, M4X, M4Y, M5A, M5B, M5C, M5E, M5G, M5H, M5J, M5R, M5S, M5T, M5V, M6G, M6J, M6K for downtown Toronto; V6A, V6B, V6C, V6E, V6G, V6Z, V5T, V7X, V7Y for downtown Vancouver. Starting in April-May 2021, this corresponds to about 24,000 businesses a month (initially only 15,000 focused on a smaller area) in the retail, food-service, and accommodation sectors.

[4] Documentation on Google Places API query options can be found here.

Out of 96 possible business types returned by the query,[5] we use "`store`," "`gas_station`," "`lodging`," "`restaurant`," "`bar`," "`cafe`," and "`night_club`." Those keywords allow us to match the North American Industry Classification System (NAICS) codes 44/45, 721, and 722 for the retail, accommodation, and food-service sectors, respectively.

2.2 Cross-section of businesses

Each query returns at most 20 places, with a flag indicating whether or not more than 20 places fit the types queried. We use this flag to design a simple recursive algorithm that finds a set of queries for which (1) each query returns no greater than 20 results and (2) a desired geographic area is fully covered.

We begin with a single large square and query the circle that circumscribes it. Whenever the results of a query indicate that there are more than 20 results, we subdivide this square into four smaller squares and requery on each. This terminates when there are no more than 20 results per query. The details are in Algorithm 1 in Appendix B. Figure 1 provides an example of the geographic units and the query results our algorithm arrives at. It shows that the higher the business density (the green dots), the finer the search grid needs to be (the squares).[6]

2.3 Time series of openings and closures

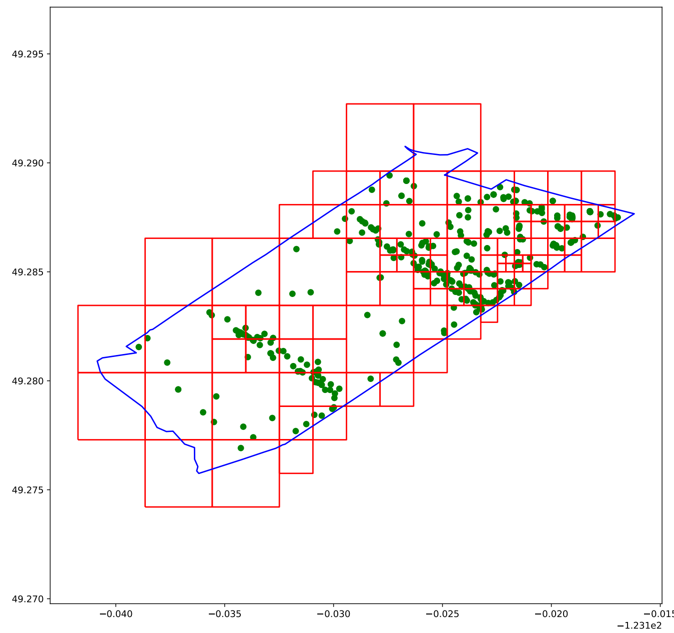
Since Google Places API returns only the most recent information and not historical data. We repeatedly scrape the same area at a certain interval (in our case, monthly)[7] to build a time series. To save on the time and cost per query, instead of beginning each month's data collection with an uninformative grid consisting of a single large square, we initialize

[5]The link here contains a full list of the supported business types, which are not mutually exclusive.

[6]We required about 1,000 queries for downtown Ottawa/Gatineau, 4,800 for downtown Toronto, 2,100 for downtown Vancouver, and 3,500 for downtown Montreal, given our chosen coverage of FSAs by city.

[7]The dataset is updated continuously, so one can consider weekly estimates, especially during a fast-paced crisis. But the use of the Google Places API requires a fixed cost per query, thus, we collected monthly data.

Figure 1: Illustration of Algorithm 1 for the keyword "`store`" in downtown Vancouver



Note: The blue shape is the bounding box of the forward sortation area with the postal code V6E. The vertical and horizontal axes represent latitude-longitude coordinates. The red squares are those inscribed in the coverage disks of each query and the green points indicate the places found. Smaller squares are required where the density of the places is higher. Data as of August 23, 2021. Our codes are provided in the replication package of Duprey et al. (2023).

Algorithm 1 by using the grid of squares resulting from the previous month's data collection.

Table 1 illustrates our classification based on the possible changes between months $t-1$ and t. We identify an exit if the business's unique identifier `place_id` is removed from the dataset. The variable `business_status` indicates whether a business is currently operational or temporarily closed.[8] The closure rate is computed as the fraction of the exiting or temporarily closing businesses compared to the operational businesses of the previous month.[9]

Likewise, we identify an entry when a new unique identifier appears in the dataset. A

[8]Appendix A compares our estimates of temporary closures with the experimental estimates from Statistics Canada. The differences in coverage granularity, the definition (enterprise versus establishment level), as well as the reliance on payroll data are such that those estimates capture no significant increases in temporary closures during the second lockdown of April 2021. Conversely, our estimates derived from Google Places capture a large heterogeneity across space, sectors, and time, with a spike of temporary closures around the second lockdown.

[9]We can also identify relocations in which two businesses have the same unique identifier but a change in address. If the relocation is outside the city for which we downloaded the data, it will be treated as an exit. If the relocation occurs within the same city, which is most likely, it is treated as a single continuously operational business unless it temporarily closes during the move.

reopening corresponds to a business previously temporarily closed that is operational again. The opening rate is computed as the fraction of entrants or reopening businesses compared to the number of operational businesses the previous month.

	Open in t with:		Temporarily	Non-existent
	$\leq$ 10 reviews	$>$ 10 reviews	closed in t	in t
Open in t-1	Continuing		Temporary closures	Exits
Temporarily closed in t-1	Reopenings			
Non-existent in t-1	Entries			

Table 1: Business openings (entries and reopenings) and closures (exits and temporary closures)

If a business is not immediately captured by Google Places upon opening it could enter the dataset at a later stage when reporting is improved. A business that was opened earlier but only recently entered the dataset is likely to have accumulated customer reviews already. Conversely, if a business is truly opening in a given month, it is unlikely to have a large number of customer reviews at that time. We require new openings in a month to have at most 10 reviews, where the cutoff is informed by a survey of businesses conducted in Ottawa (Duprey et al., 2022).

3 Stylized facts on business dynamics

3.1 Temporary closures contribute to a faster recovery of business entry rates

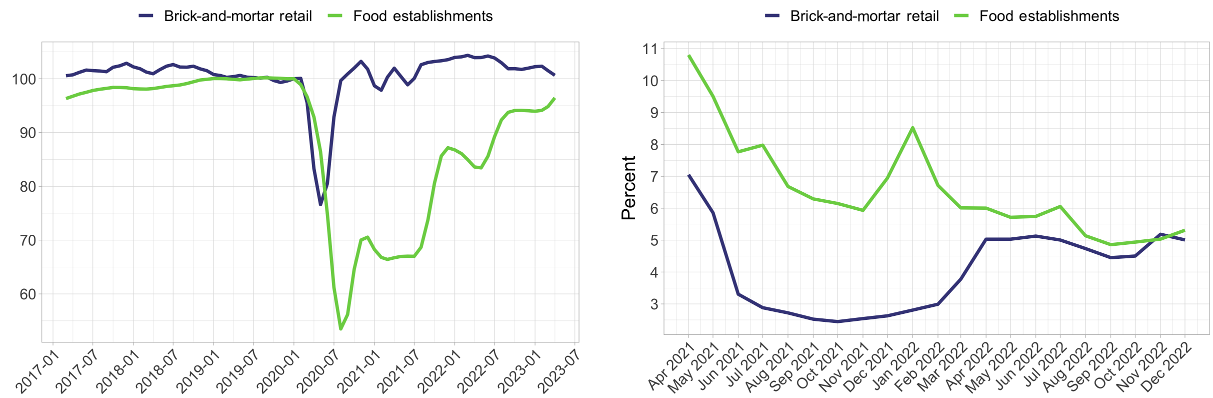
We tracked businesses in downtown Toronto, Vancouver, Montreal, and Ottawa from April-May 2021 onwards. Thus the beginning of our data corresponds to lockdowns and stay-at-home orders due to the third wave of COVID-19, which transmitted the Delta variant. More than half of the total business openings in June 2021 were driven by reopenings rather than by new business entries (Duprey et al., 2023). For Ottawa, the majority of reopenings and entries in the summer of 2021 were confirmed by a survey of businesses (Duprey et al., 2022). The importance of reopenings for the speed of the post-pandemic economic recovery is also in line with Crane et al. (2022) and Kurmann et al. (2021).

The pandemic in Canada had a heterogeneous impact across sectors. The food- and beverage-service sector experienced a 47% decline in household expenditures by mid-2020 and did not recover to prepandemic levels before 2022. This was partly a substitution for home consumption, with a 5% increase in expenditures on food and beverages consumed at home, by mid-2020 (Statistics Canada Table: 36-10-0124-01). Conversely, the impact on the retail sector was smaller and shorter, with a recovery from a 30% decline occurring by mid-2020 (Statistics Canada Table: 36-10-0434-02). Figure 2 displays detrended consumer spending against temporary business closures for each sector. The food-service sector experienced a sharper drop in consumer spending, a slower recovery, and a higher share of temporarily closed businesses, at 11% during the third wave of COVID-19. Conversely, the retail sector experienced a smaller and short-lived drop in consumer spending, with only 7% of businesses temporarily closed during the third wave.[10]

Figure 3 further breaks down the evolution of the status of businesses in the food-service sector that were initially temporarily closed in April-May 2021 during the lockdown associated with the Delta variant. Overall, about 40% of these businesses reopened as soon as COVID-19 restrictions were lifted, with another 20% taking more time to reopen. Bars were the fastest to reopen, with about half having already reopened by July 2021. Similarly, the emergence of the Omicron variant, in December and January 2022, was associated with new restrictions, leading to more temporary closures in December 2021 and reopenings in

[10] If temporary closures were permanent exits, then those businesses should not appear in the UK registry after they exited, given the registry's yearly registration fees and its penalty fees for late status updates. Duprey et al. (2023) show that the share of temporarily closed businesses in a sample of Google Places data merged with the UK business registry is the same as a broader sample not merged with the registry. This implies that temporary closures most likely capture businesses expecting to reopen later, and not permanent exits.

Figure 2: Consumer spending and temporary closures around the COVID-19 pandemic



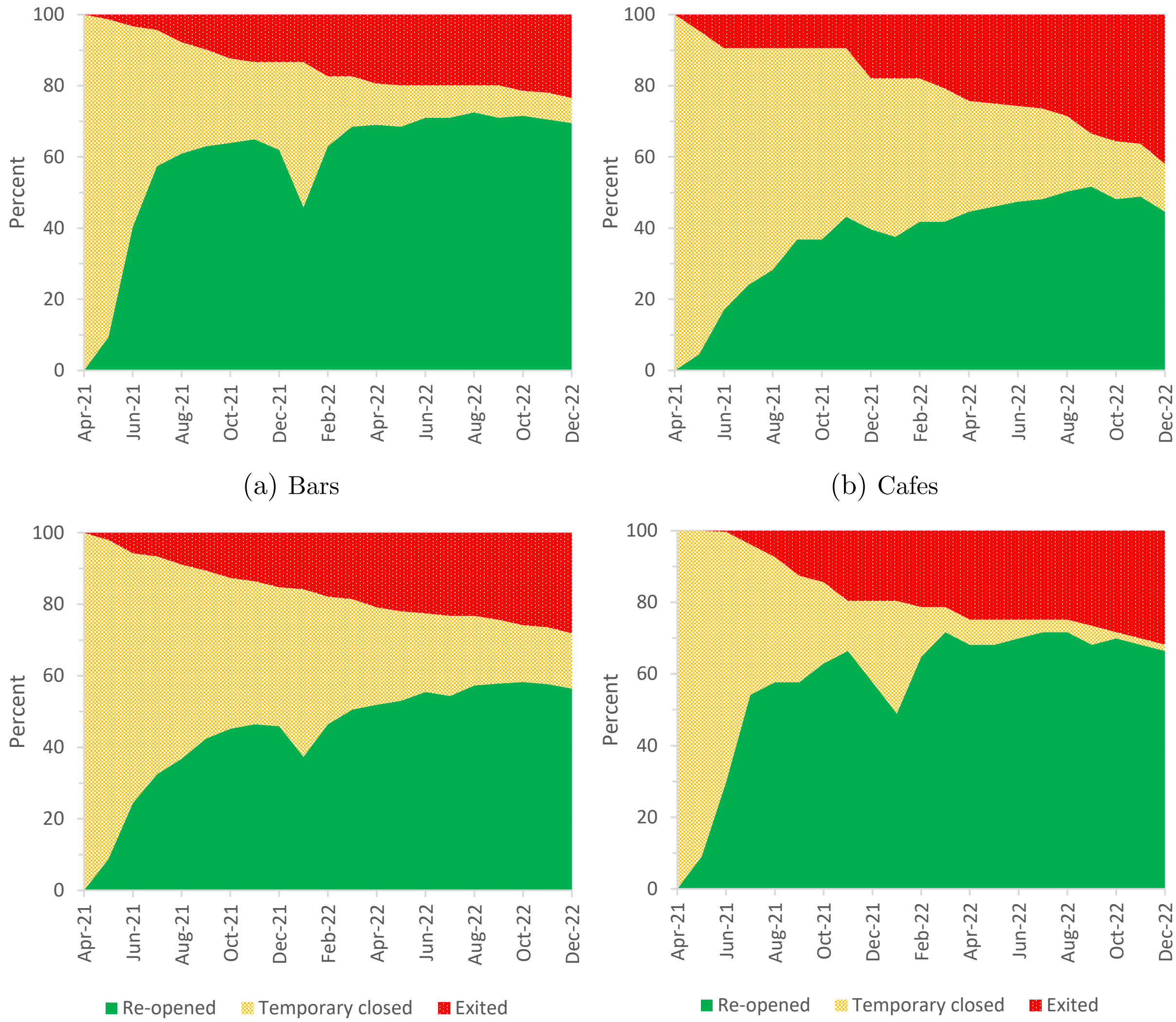
(a) Reduction in real consumer spending

(b) Temporary business closures

Note: The chart on the left shows consumer spending on non-online retail (blue) and spending at all food-serving establishments, excluding accommodation providers (green), from Statistics Canada (Tables 20-10-0056-01 and 36-10-0124-01). The series were deflated using the consumer price index (Table 18-10-0006-01), detrended with a linear trend between 2017 and 2023 and normalised with January 2020 = 100. The chart on the right shows the temporary closure rates in the two sectors derived from Google Places, using the method in Section 2.

January 2022. Some of the businesses that temporarily closed in April-May 2021 had to temporarily close again in January 2022, during the Omicron wave. Government support for temporarily closed businesses during the COVID restrictions may have contributed to a faster recovery. Of those businesses that temporarily closed during the 2021 lockdown, only about one-third had permanently exited by the end of 2022. Only one-fourth of the bars and restaurants that had been initially temporarily closed eventually exited, but this was about half for cafes, the category in our sample that was the most severely hit.

Figure 3: Evolution of the status of businesses temporarily closed in April-May 2021



(a) Bars

(b) Cafes

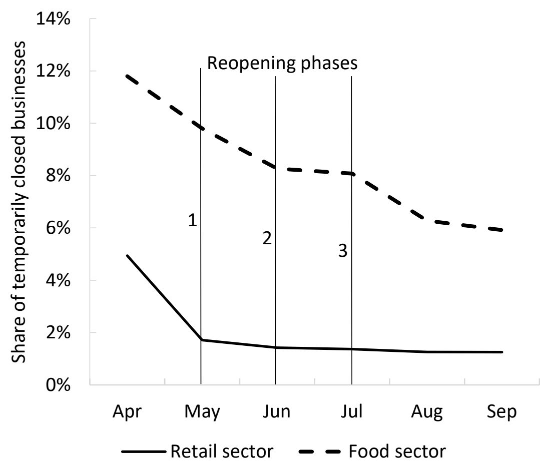
(c) Restaurants

(d) Night clubs

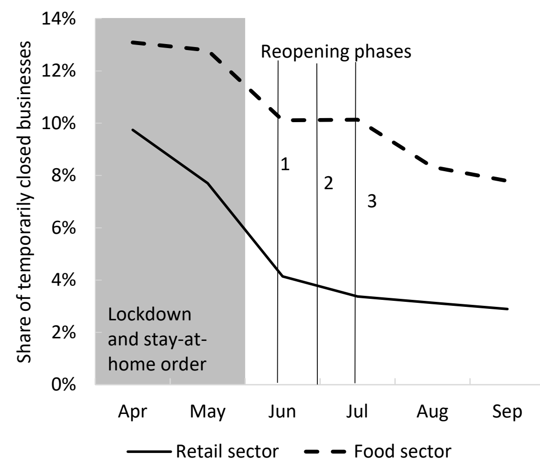
Note: The figure displays the evolution of the status of 1,008 businesses in the food-service sector identified by Google Places as temporarily closed at the beginning of our data collection period in April 2021, during the third wave of COVID-19 (Delta variant) associated with lockdowns and stay-at-home orders. The drop in the number of businesses reopening around December 2021 corresponds to the fifth wave of COVID-19 (Omicron variant) that led to new restrictions in parts of Canada. Businesses that were temporarily closed in April 2021 could either remain temporarily closed, reopen, or exit in the subsequent months. The few cases where businesses were identified in a given month as having permanently exited but that reappeared in the dataset in subsequent months were relabelled as temporary closures prior to reopening.

The timing of the pandemic restrictions and the cross-section of business types across cities confirms the relevance of our dataset on business dynamics during the pandemic. Figure 4 displays the share of businesses identified as temporarily closed, by business type and city, around the restriction dates. Figure C.1 in Appendix C displays entry and exit rates split

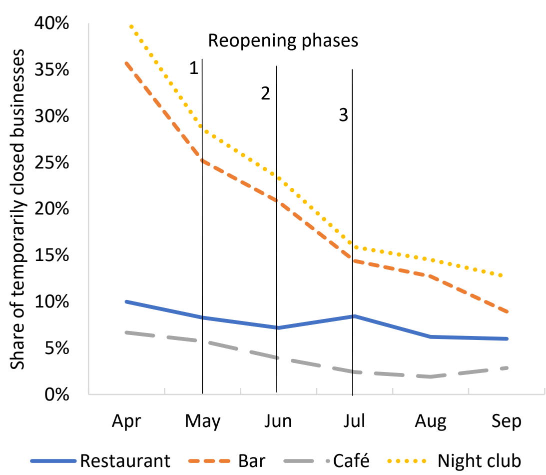
Figure 4: Evolution of the rate of businesses temporarily closed by sector in 2021



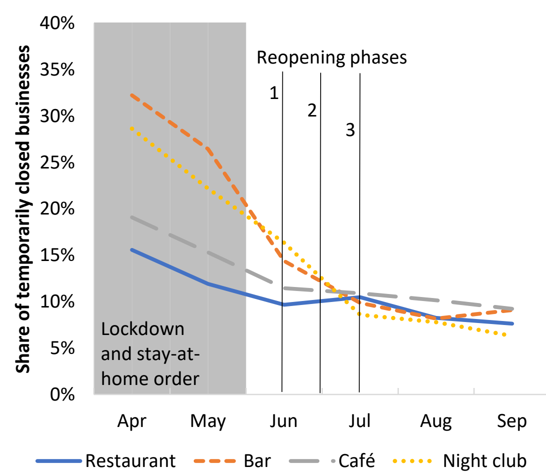
(a) Retail and food service: Vancouver



(b) Retail and food service: Toronto and Ottawa



(c) Food-service breakdown: Vancouver



(d) Food-service breakdown: Toronto and Ottawa

Note: The figure displays the monthly rate of temporarily closed businesses, derived from Google Places, for Vancouver (British Columbia), and Toronto and Ottawa (Ontario). The vertical shading and lines correspond to the timing of the provincial lockdowns and phased reopenings, as detailed in Table D.1. The retail sector corresponds to NAICS 44-45. The food-service sector corresponds to NAICS 722 and is the aggregation of the results by the keywords `bar`, `cafe`, `restaurant`, and `night_club`. In April, we did not collect data for any of the food-service subsectors for Toronto. Data for the retail sector for the month of April is only an estimate based on a smaller sample.

by business type and city during the third wave of COVID-19, with the Delta variant.[11]

The province of British Columbia (where Vancouver is located) did not have a lockdown in April 2021, with stores largely remaining open. In fact, the share of retail businesses in Vancouver that were temporarily closed was only about 5% in April (Figure 4a). Thus, we observe fewer entries and exits and almost no reopenings in Vancouver for the retail sector, compared to cities in other provinces (Figure C.1a). Most restrictions in Vancouver targeted social gatherings, with 40% of night clubs, 35% of bars, and 10% of restaurants temporarily closed in April 2021 (Figure 4c). Major restrictions were lifted in May (for restaurants) and July (for nightclubs). As expected, we observe larger reopening rates in May and July in Vancouver (Figure C.1e and C.1f), with some nightclubs reopening earlier, likely if they were also serving food as restaurants.[12]

Conversely, the province of Ontario experienced a lockdown and a stay-at-home order starting in April 2021. At least 10% of businesses in the retail sector and about 15% in the food-service sector were temporarily closed in Toronto and Ottawa (Figure 4b). The major restrictions were lifted in June (for retail and restaurants) and July (for restaurants and nightclubs). Reopenings in the retail sector peaked in June (Figure C.1a), with the share of temporarily closed retail stores falling the most that month (Figure 4b). For the food-service sector, more restaurants (+5 percentage points) and cafes (+15 percentage points) were temporarily closed in April in Ontario during the lockdown than in British Columbia without the lockdown (Figure 4c and 4d). Reopenings peaked in June in Toronto and Ottawa, one month later than in Vancouver, which started to reopen its food-service sector

[11]Table D.1 in Appendix D provides a timeline of the changes in the restrictions affecting the retail and food-service sectors in the provinces of British Columbia (for Vancouver) and Ontario (for Ottawa and Toronto). We started collecting information at the end of the post-lockdown restrictions for Montreal, such that we did not include it in Figure 4, for instance. Our narrow geographical and sectoral focus prevented us from providing direct comparisons with publicly available official statistics on entry and exit rates, as the data coverage does not match. For a sample of the UK data, Duprey et al. (2023) fuzzy-merged data from Google Places with the UK registry, using the names of the establishments with a success rate of 40%.

[12]Note that businesses identified as night clubs were not all temporarily closed because many of them were also simultaneously self-identified as restaurants, for instance, if a restaurant had a dance floor or if a night club served food. For the same reason, if some nightclubs did take-out or had seated-only guests, some reopenings for these establishments started before the official reopening.

in May (Figure C.1b). In Ontario, for the subset of sectors and areas where we have data for May, there was a sharp increase in reopenings, from close to zero in May, to a peak in June, especially for bars, cafes, and night clubs (Figure C.1c, C.1d and C.1f).

Overall, we confirm the importance of temporary closures during the COVID-19 pandemic. Our data on temporary closures line up with the timing of the restrictions and their lifting, with reopenings contributing more to business entries in cities that endured the most severe business restrictions.

3.2 Customer reviews correlate with the changes in business status and job vacancies

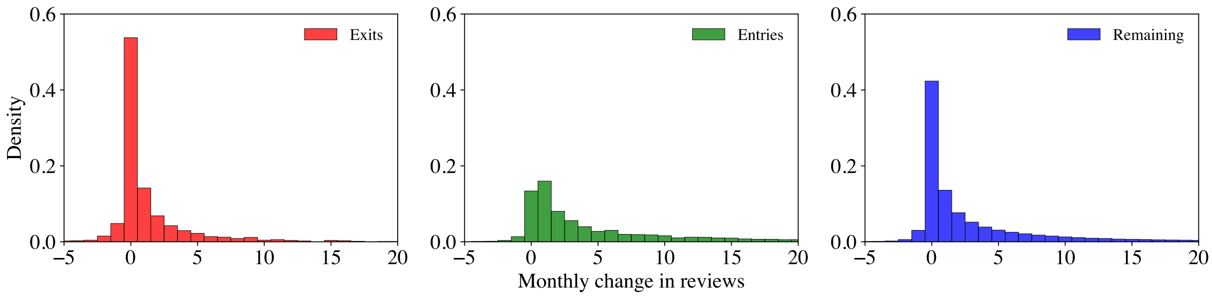
In the dataset of the retail, service, and accommodation sectors for the four main cities in Canada, about 80% of businesses had at least one customer review. We provide preliminary evidence that customer reviews can reveal valuable information associated with business dynamics.

First, we observe in Figure 5a that businesses that exited (or entered) exhibit statistically different distributions in their number of new reviews when compared to businesses that remained operational. Namely, when compared to businesses that remained open, entries tended to accrue more reviews, while exits gained fewer reviews.[13] As a result, changes in the number of reviews may be a useful—and unique—proxy for a business's level of activity.

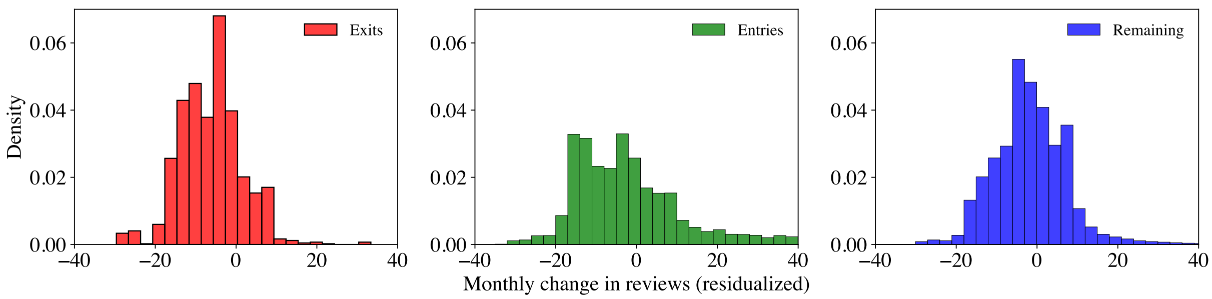
In addition, among businesses that remained operational, those that exited *in the next period* tended to have fewer customer reviews in *the current* period. Thus, the change in the number of reviews can also be a potential early indicator of a business exit. Figure 6a shows the distribution of the number of new reviews in a given month if a business remained

[13]Note that the number of new reviews was computed over the month in which we observed an entry or an exit. Therefore, the smaller number of reviews for exiting businesses may have resulted in both from fewer reviews per day and fewer days of operation before exiting during that month. In addition, we observe instances where the number of reviews decreased over a month, for instance if users or businesses deleted reviews.

Figure 5: Entries (exits) accrue more (fewer) reviews than remaining businesses do



(a) Raw numbers



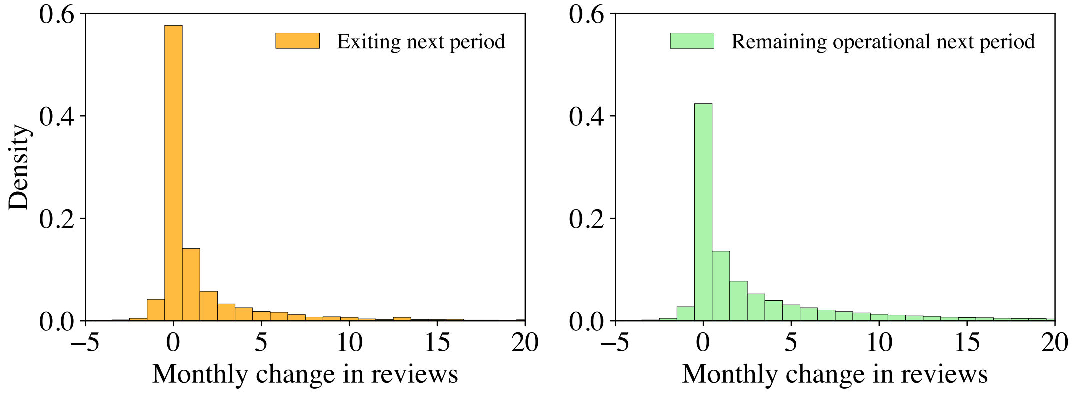
(b) Residualized numbers

Note: Data collected from downtown Toronto, Vancouver, Montreal, and Ottawa, cover about 400,000 observations from Google Places in the retail, food-service, and accommodation sectors, from April 2021 to December 2022. Entries and exits were assessed according to the classification in Table 1. Panel (a) displays the change in the number of new reviews for businesses exiting, entering, and remaining operational. Panel (b) displays the equivalent residuals from Equation (1) net of temporal, sectoral, and location fixed effects.

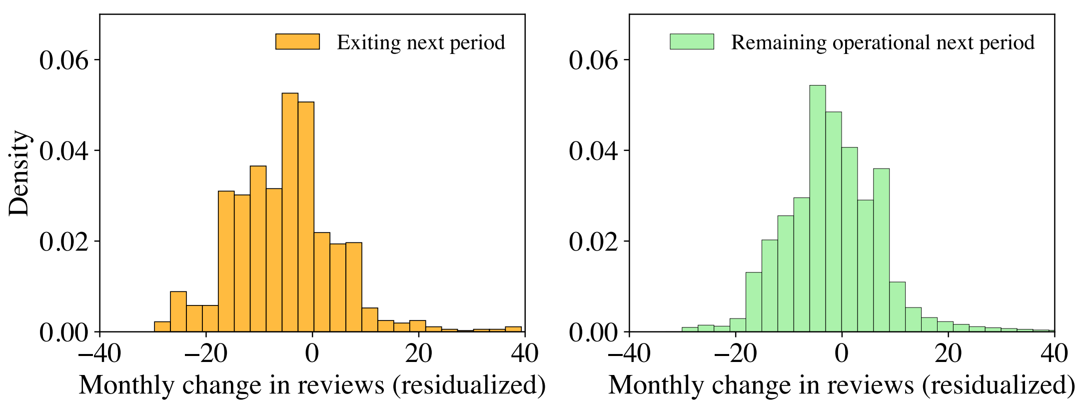
operational or exited in the subsequent month. We find a statistically significant difference in the distribution, suggesting that businesses that were generating fewer reviews during a month were more likely to exit over the next month.

So far, Figures 5a and 6a use the raw numbers for the changes in reviews. However, these observed differences could be driven by time, sector, and location fixed effects. Alternatively, we can regress a business's change in their number of reviews on the time, sector, and location

Figure 6: Businesses with more ratings are more likely to remain operating



(a) Raw numbers



(b) Residualized numbers

Note: Downtown Toronto, Vancouver, Montreal, and Ottawa, covering about 400,000 observations, from Google Places, in the retail, food-service, and accommodation sectors, from April 2021 to December 2022. Remaining and exiting businesses were assessed according to their classification in Table 1. Panel (a) displays the change in the number of reviews for businesses exiting or entering the next month. Panel (b) displays the equivalent residuals from Equation (1) net of temporal, sectoral, and location fixed effects.

dummy variables as

$$\begin{aligned}\text{ChangeInReviews}_{it} = &\text{IsFood}_i + \text{IsAccommodation}_i + ... \\ &+ \text{IsInToronto}_i + \text{IsInMontreal}_i + ... \\ &+ \mathbb{1}\{t=1\} + ... + \mathbb{1}\{t=20\} + \varepsilon_{it},\end{aligned} \tag{1}$$

where i indicates a unique business and t indicates an index of a month in which we collected data.

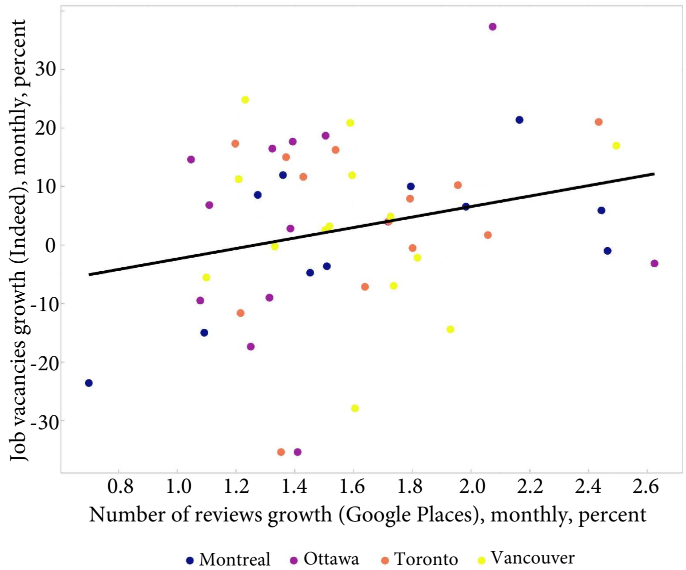
Figures 5b and 6b now display the residuals ε_{it}, instead of the change in the number of reviews.[14] We find that the same qualitative differences and the resulting distributions remain statistically different from each other.

These observations can also be validated through another data source, this one on job vacancies. Figure 7 shows how the monthly growth in the number of reviews from Google Places for establishments in each city in our sample correlates with the monthly growth of all job vacancies per city from the job-listing website 'Indeed.' Despite the coverage difference in the two datasets, we find a strong positive relationship at the city/month level, suggesting that businesses that were generating more reviews were also the ones that were most dynamic in terms of employment growth. This may be an economically significant aggregate effect if one considers that the sectors we covered account for up to 20% of the total employment in Canada (respectively 12%, 6% and 1.5% of total employment in the retail, accommodation, and food-service sectors; see Statistics Canada Table 14-10-0202-01). A similar positive correlation was obtained when restricting both datasets to cover the food-service and accommodation sectors only, at the cost of losing the cross-city comparisons as the breakdowns by both sector and city are not available from our 'Indeed' dataset. Better-rated businesses, on average, are also correlated with more job listings. This is consistent with Bahaj et al. (2022), who find that job vacancies from the website 'Indeed' correlated with post-pandemic

[14] The coefficient estimates are left for Appendix E.

firm creation in the UK, and also with Kurmann et al. (2021), who find that small businesses reopening after COVID were key drivers of employment dynamics.

Figure 7: A higher number of new reviews correlates with an increase in the number of job vacancies



Note: Data from April 2021 to December 2022. For Google Places, data averaged across the downtowns of the four cities for the retail, food-service, and accommodation sectors. For Indeed, data averaged across the four metropolitan areas for all business types.

3.3 Temporary closures correlate with subsequent lower consumer prices

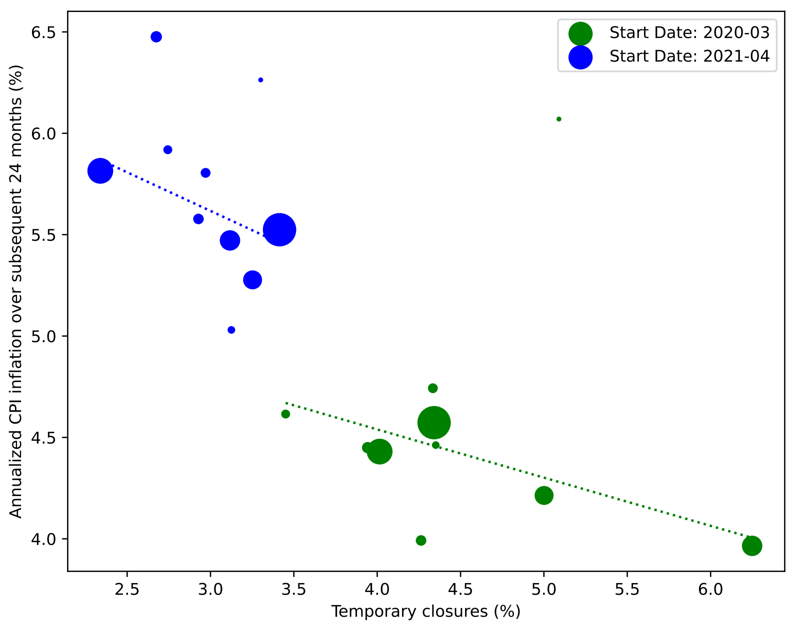
When a negative shock hits, temporary closures may save on business entry costs, thus subsequently lowering consumer prices: reopening can be less costly than having a new business pay the startup costs to replace a closed one.[15] If so, we expect a negative correlation between the fraction of temporarily closed businesses and subsequent inflationary pressures in the affected sectors.

Our Google Places dataset does not include establishment-level prices. So we instead use

[15] According to estimates by the restaurant management software company Toast, Inc. the average cost is 80,000 $ to 300,000$ for opening a cafe Toast Inc. (2024b), 175,000$ to 700,000$ for a small restaurant Toast Inc. (2024d), 110,000$ to 850,000$ for a bar Toast Inc. (2024a) and 240,000$ and 840,000$ for a night club Toast Inc. (2024c).

aggregated Statistics Canada data on provincial consumer price inflation and temporary closures.[16] Figure 8 shows that provinces with a higher temporary closure rate across all sectors during the March 2020 and April 2021 lockdown experienced comparatively lower CPI inflation two years out. The correlation, weighted for the number of businesses in each provinces, is -.70 and -.63 for the first and second lockdown, respectively.[17] We interpret this as indicative evidence for our channel: during the COVID-19 pandemic, temporary closures sustained capacity, allowing for a faster recovery and subsequently less pressure on the price level. The next section introduces a model to formalize and assess this possible channel.

Figure 8: A higher rate of temporary closures correlates with lower subsequent inflation



Note: The provincial cross-sector temporary closure rate is taken from Statistics Canada and is assessed at either March 2020 (the first lockdown, green bubbles) or April 2021 (the second lockdown, blue bubbles). Each bubble represents a Canadian province, with the size of the bubbles proportional to the number of businesses in each province. Source: Statistics Canada, experimental estimates for business openings and closures (Table: 33-10-0270-01) and monthly provincial CPI inflation (Table: 18-10-0004-13).

[16] Appendix A displays the Canada-wide time series of temporary closures for the accommodation and retail sectors built by Statistics Canada with an explanation of the differences with our Google Places dataset, e.g. regarding granularity and coverage.

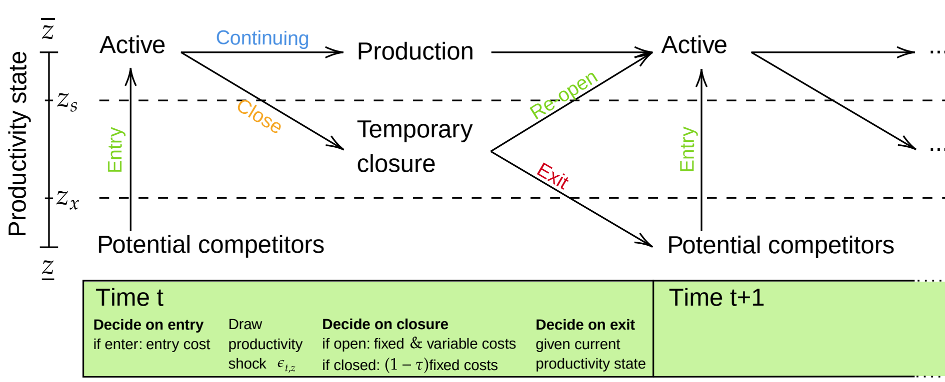
[17] When using the Google Places data instead, we find a similar negative correlation with a six and twelve months horizon. However, the macro exercise becomes more limited: we have data only for the reopening phase of the second lockdown in 2021, we have only two sectors in the main cities of only three provinces, and we do not have the corresponding city- and sector-level inflation measures.

4 Modelling temporary closures

Our new establishments-level data highlights that some firms permanently shut down in response to an aggregate shock while other firms only temporarily close their operations. Data on the establishment reviews presented in the previous section also indicate that preventing productive businesses—that experience continued demand for their services, approximated by their number of reviews—from permanently exiting could support employment. This behaviour supports the idea that, following a temporary decline in demand, as observed during the pandemic, mothballing operations is also a rational response for firms. To prevent permanent exits and avoid a sluggish recovery, it may be desirable for governments to subsidize temporary closures.

We capture these observations in a firm dynamics model as first outlined in Hopenhayn (1992) and Hopenhayn and Rogerson (1993). We depart from the baseline model in one crucial way: At the beginning of each period, firms observe their realised productivity and decide whether to temporarily close their operations, saving a share of the fixed cost, or to continue operating. The timing of the model is represented in Figure 9. Our model provides evidence for fast recoveries when firms have, in the spirit of Dixit et al. (1994), the option to temporarily shutting down production.

Figure 9: Timing of the model of firm dynamics extended to temporary closures



4.1 Individual firm production

Firms produce in a competitive market, taking the market price, p, and wages, w, as given. Each firm uses only labour to produce and has an idiosyncratic productivity state, z. The productivity state of the firms is described by a persistent stochastic auto-regressive process,

$$z' = \rho_z z + \epsilon_z, \tag{2}$$

where $\rho_z \in (0, 1)$ is the persistence parameter and $\epsilon_z \sim N(0, \sigma_z^2)$ are idiosyncratic and identically distributed shocks. The firm's period profit function when the firm is producing is

$$\pi(p, z) = \max_n \left[p \exp(z) n^\alpha - wn - wf \right]. \tag{3}$$

The labour cost, wn, varies with the size of the firm, with fixed cost wf scaled by the size of the firm. The optimal labour choice in this case is $n^* = (\frac{\alpha p \exp(z)}{w})^{\frac{1}{1-\alpha}}$ and the optimal output for a firm is $y^* = z(\frac{\alpha p \exp(z)}{w})^{\frac{\alpha}{1-\alpha}}$.

At the beginning of each period, after observing the firm's current period productivity realisation, z, the firm's management decides whether to produce or to temporarily close for the current period. When the firm exits temporarily, it can save on fixed costs, τwf, such that the fraction $(1-\tau)$ is the cost of maintaining the business while it is closed temporarily, for instance through partial wage payments, tax payments, or upkeep. The firm solves the following optimization problem of whether to produce or to temporarily close down their production,

$$\max\{\pi(p, z); \; -(1-\tau)wf\}. \tag{4}$$

At the end of every period, the firm's management decides whether to exit permanently or to continue operating for the next period. When the firm permanently exits, the future value of the firm is 0. Equation (5) describes the firm's value function,

$$V(p,z) = \max\{\pi(p,z);\ -(1-\tau)wf\} + \beta \max\{\mathbb{E}(V(p',z'));\ 0\}. \tag{5}$$

Proposition 1. *Firms below productivity state z_s will exit production temporarily, while firms below productivity state z_x will exit permanently. Given $\tau \in (0,1]$, equilibria exist where $z_x < z_s$ in a given period.*

Proof. Assume z_x is at an arbitrary level $\mathbb{E}(V(p', z'|z_x)) = 0$ and $p = p'$. This means that for a slightly higher productivity $z^+ = z_x + \delta$, $\mathbb{E}(V(p, z'|z^+)) > 0$. At this productivity level, however, $\pi(p, z^+) < 0$ is possible as the firm may have a positive expectation about the next period's productivity outweighing any losses from the current period. This will be the case when $z_x < 0$ as then $\mathbb{E}(z') > z_x$ and $\mathbb{E}(\pi(p, z')) > \pi(p, z_x)$. It is then clear that there exists a value of τ where the firm will prefer to stay closed at the productivity level $z_s \geq z^+ > z_x$. $\square$

4.2 Aggregate dynamics

We discretize the idiosyncratic productivity space for firms over n_z. The law of motion of all firms in the economy is driven by the transition matrix of firms between states $\Pi_{z'|z}$ and the choice of firms to exit $\mathbb{I}_{z>z_x}$. We assume that new firms enter by paying entry cost C_e, given by

$$C_e = \left(\frac{E}{E^*}\right)^{\xi} c_e w\ . \tag{6}$$

We choose a convex parameter for the entry cost ξ to capture that a lot of demand for entry will contest the input factors required for entry and increase the cost of a firm's entry.[18]

Here E^* is the steady state level of entry, meaning that in the steady state, $c_e w$ is the entry cost paid by a firm, and c_e is an exogenous cost controlling for the amount of labour needed to set up the firm. Firms enter the market in the next period and draw their initial

[18]Our main qualitative results also hold for the linear cost of entry.

productivity state from the long-run distribution of productivity z, Π_0. Firms optimally enter until the expected value of entering equals its cost,

$$\left(\frac{E}{E^*}\right)^{\xi} c_e w = \beta \mathbb{E}\left(\Pi_0 V(p', z')\right) \ . \tag{7}$$

In a steady state, Equation (7) simplifies to $c_e w = \beta \Pi_0 V(p, z)$.

Finally, the law of motion of all firms in all states, M, is

$$M' = \Pi_{z'|z} \, \mathbb{I}_{z>z_x} \, M + \Pi_0 E \ . \tag{8}$$

M is the vector of all firms ordered along discretized states. Here $\mathbb{I}_{z>z_x}$ refers to an $n_z \times n_z$ matrix, where the rows and columns representing z above z_x form an identity submatrix and all other values are 0. In a steady state, we can solve for the equilibrium firm distribution as a function of entries, $M = (\Pi_0 E)(I - \Pi_{z'|z}\mathbb{I}_{z>z_x})^{-1}$, with I as an identity matrix.

These allow us to compute the equilibrium aggregate supply. Aggregate supply Y is the total production of all firms in the market. It is the sum of all firms that choose to produce $\mathbb{I}_{z>z_s}$, weighted by the vector of existing firms in all states, M, and expressed as

$$Y = \int_{\underline{z}}^{\bar{z}} (\mathbb{I}_{z>z_s} M y^*) dz = \int_{z_s}^{\bar{z}} M z \left(\frac{\alpha p \exp(z)}{w}\right)^{\frac{\alpha}{1-\alpha}} dz \ . \tag{9}$$

Here, $\mathbb{I}_{z>z_s}$ refers to an $n_z \times n_z$ matrix where the rows and columns representing z above z_s form an identity submatrix and all other values are 0.

As in Hopenhayn (1992), and Hopenhayn and Rogerson (1993), the equilibrium price, p, in the market is then given by the exogenous demand, $\bar{D}$, over the supply,

$$p = \frac{\bar{D}}{Y}. \tag{10}$$

We can also calculate aggregate firm employment. This is the sum of the employment of firms operating, the payments on the fixed costs for temporarily closed firms, and the entering firms' payments to enter the market, given by

$$L = \int_{z_s}^{\bar{z}} \mathbb{I}_{z>z_x} M n^*(z) dz + \int_{z_x}^{z_s} (\mathbb{I}_{z>z_x} - \mathbb{I}_{z>z_s}) M(1-\tau) f dz + \frac{EC_e}{w} \ . \tag{11}$$

Aggregate employment enables us to determine the wage in the labour market. Concretely, we assume a stable supply. As a result, the wage in a given period is determined by variations in demand,

$$\frac{w}{w^*} = \left(\frac{L}{L^*}\right)^{\zeta} \ . \tag{12}$$

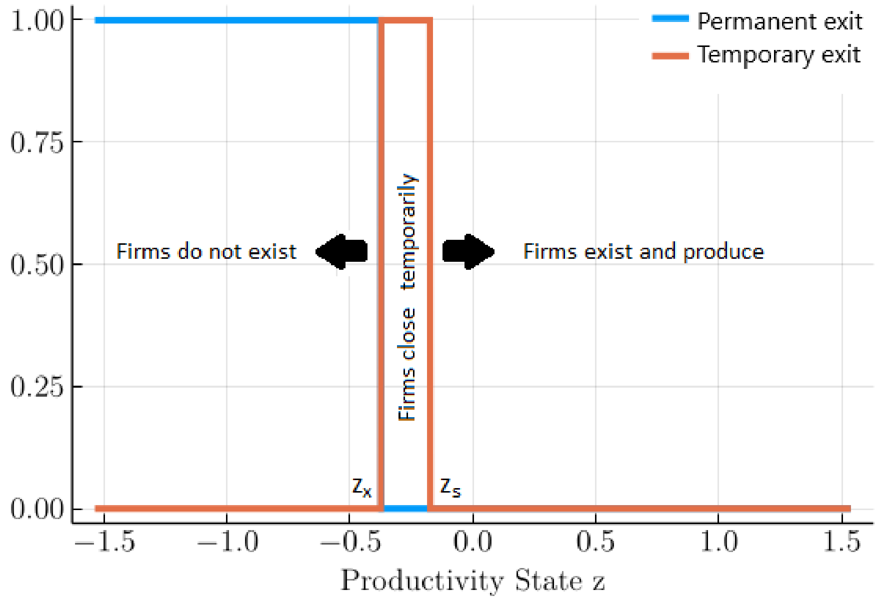
The parameter ζ captures the elasticity of wages to changes in demand and, thus, is the inverse of the Frisch elasticity.

4.3 Simulation approach

We perform simulations for the retail and food-production sectors that experienced a severe decline in demand—proxied by consumer spending—and an increase in temporary closures (Figure 2). As in the data, we simulate a stronger and more-persistent effect for food-service establishments. This phenomenon is also observed in the yearly employment data (Statistics Canada Table 14-10-0202-01), with a 7% decrease in the number of retail jobs in 2021, compared to 2020, that fully recovered in 2021, versus a 23% drop for food services and drinking places in 2020 that had not fully recovered as of 2022.

We calibrate the model to match the long-run entry rate and the measured temporary closure rate in equilibrium. The calibration parameters are in Table 2. The calibrated steady-state entry and the permanent-exit rate is 1%, to match the monthly entry rates in the food-service, accommodation, and retail sectors reported by Statistics Canada (2020). The steady-

Figure 10: Firms' status as a function of their productivity in the steady state



Note: The steady-state of the model showing firms' status as a function of their productivity state. Status is 1 for firms that exit (permanently, in blue, or temporarily, in red) and status is 0 for firms that continue operating, given their productivity realisation, z.

state temporary closure rate is calibrated to 5%, as inferred from our data in Figure 2b. Figure 10 shows that, in our model calibration, the model steady-state exhibits idiosyncratic productivity states for firms that choose to exit temporarily. Of these temporarily exited firms, the more productive choose to remain in the market at the end of the period to receive a new realisation of their idiosyncratic productivity in the next period, while the firms with lower idiosyncratic productivity realisations choose to exit permanently at the end of the period.

We simulate the decline in demand proxied by consumer spending (Figure 2a) as an MIT shock, following Boppart et al. (2018). Thus, we assume that the decline in demand is known from 2020 onwards and firms expect demand to go back to equilibrium in July 2023. Concretely, we solve the optimal entry and exit paths for firms of all states, iteratively from the deviations in equilibrium demand $\bar{D} = 100$ and the equilibrium price. We assume that after the observed changes in demand, demand stays at the equilibrium level $\bar{D} = 100$ for the rest of time. Our iteration converges to a dynamic equilibrium consisting of the state

Parameter	Value	Description
β	0.9966	Monthly discount factor for an annual discount factor of 0.96
ψ_m	0.00	Idiosyncratic mean log productivity
ψ_ρ	0.95	Persistence of idiosyncratic firm productivity process
ψ_σ	0.20	Volatility of idiosyncratic firm productivity shocks
α	0.67	Exponent on labour
c_e	2.65	Equilibrium entry cost
c	0.20	Equilibrium fixed cost
ξ	2.00	Convex increase of entry cost
w	2.00	Wage
ζ	Food service: 0.35 Retail: 0.47	Estimated separately with details in Appendix F.1
$\bar{D}$	100	Normalised equilibrium demand
τ – Share of the fixed cost that can be saved when temporarily shutting down		
	0.2750	Baseline
	0.0000	First counterfactual - no temporary closures
	0.3025	Second counterfactual - subsidised temporary closures

Table 2: Model calibration

vector of firms, the path of entrants, the decisions for permanent and temporary exits, and the price, $\{M, \mathbb{1}_{z>z_x}, \mathbb{1}_{z>z_s}, p\}_{t=0}^{\infty}$.[19]

5 Simulation results and policy implications

We show the impact of the temporary closures in our model by comparing the dynamics of entries, exits, prices, and firm numbers, during the COVID-19 pandemic, to two counterfactuals. The scenarios differ only in the calibration of the share, τ, of the fixed costs that can be saved when temporarily shutting down, as shown in Table 2. In the first counterfactual, between February 2020 and January 2022, we do not allow firms to temporarily close. This is equivalent to calibrating to zero the share of the fixed costs that can be saved when temporarily shutting down: that is, a temporary closure yields no savings. In the second counterfactual, firms that choose to temporarily close from 2020 until January 2022 save an additional 10% in their fixed costs. This approximates the additional government subsidies that would have incentivized more firms to only temporarily shut down production. Both counterfactuals assume that, from February 2022 onwards, firms can temporarily close and

[19] Further computational details are in Appendix F.2.

save the baseline share of their fixed costs. This ensures that both counterfactuals converge to the same steady state as the baseline scenario in the long run.

The top row in Figure 11 shows our main variable of interest, the share of temporary closures for the food-service (lefthand side) and the retail sectors (righthand side).[20] As expected, the simulated decline in demand in the baseline scenario (plain line)—replicated from the data, see Figure 2a—leads to an increase in the share of firms temporarily closing. The dynamics across sectors differ due to the size of the demand shock. For brick-and-mortar retailers, the smaller size of the initial negative demand shock leads more low-productivity firms to decide to close temporarily instead of exiting permanently, such that they are ready to reopen once the aggregate shock passes. In contrast, the large size of the negative demand shock for food-serving establishments initially leads to relatively more-permanent exits for low-productivity firms rather than temporary closures in the hope for a better productivity draw in the next period. As the initial aggregate shock passes, higher-productivity firms receiving negative shocks enter the productivity parameter space where it is optimal for them to close temporarily, driving the temporary closure rate up. In the counterfactual case with stronger incentives to close temporarily (long-dashed orange line), we observe similar dynamics with a higher rate of temporary closures. In the counterfactual case where temporary closure is not possible for two years (short-dashed red line), the temporary closure rate is zero by assumption.

The bottom row in Figure 11 shows the number of firms where the steady state has been normalised to one hundred, so that changes can be interpreted as percentages of the steady state. In the baseline scenario (plain line), the large shock in the food-service sector leads to the number of firms falling by 6%. The option to temporarily close reduces this fall, compared to the counterfactual without temporary closures (short-dashed red line), by around 2 percentage points. As expected, more firms would have survived in the counterfactual where

[20]The dynamics of entry, permanent exit, equilibrium prices, and employment are plotted in Figure F.2 for the baseline and the two counterfactuals are in Appendix F.3.

temporary closures are further subsidised (long-dashed orange line). The response of the retail sector in our model is particularly interesting. Figure 2a shows that, in this sector, the negative demand shock was smaller and shorter-lived, followed by an increase in demand as consumers started to spend more in retail shops to substitute for other experiences such as outside food consumption. The shock, therefore, leads to an increase in temporary closures, but this increase creates incentives for new entrants to come into the market in the hope of receiving a better productivity draw at an increased price level. The increased entries and decreased permanent exits shown in Figure F.2 in Appendix F confirm this interpretation. As a result, the total number of firms varies less but increases in the cases where we allow for temporary closures. An increase in business creation in the retail sector, during the pandemic, has been well documented in the data (Decker and Haltiwanger, 2023; Duguid et al., 2023) and opportunities created for entrants by businesses temporarily closing, as predicted by the model, may contribute to explaining this phenomenon.

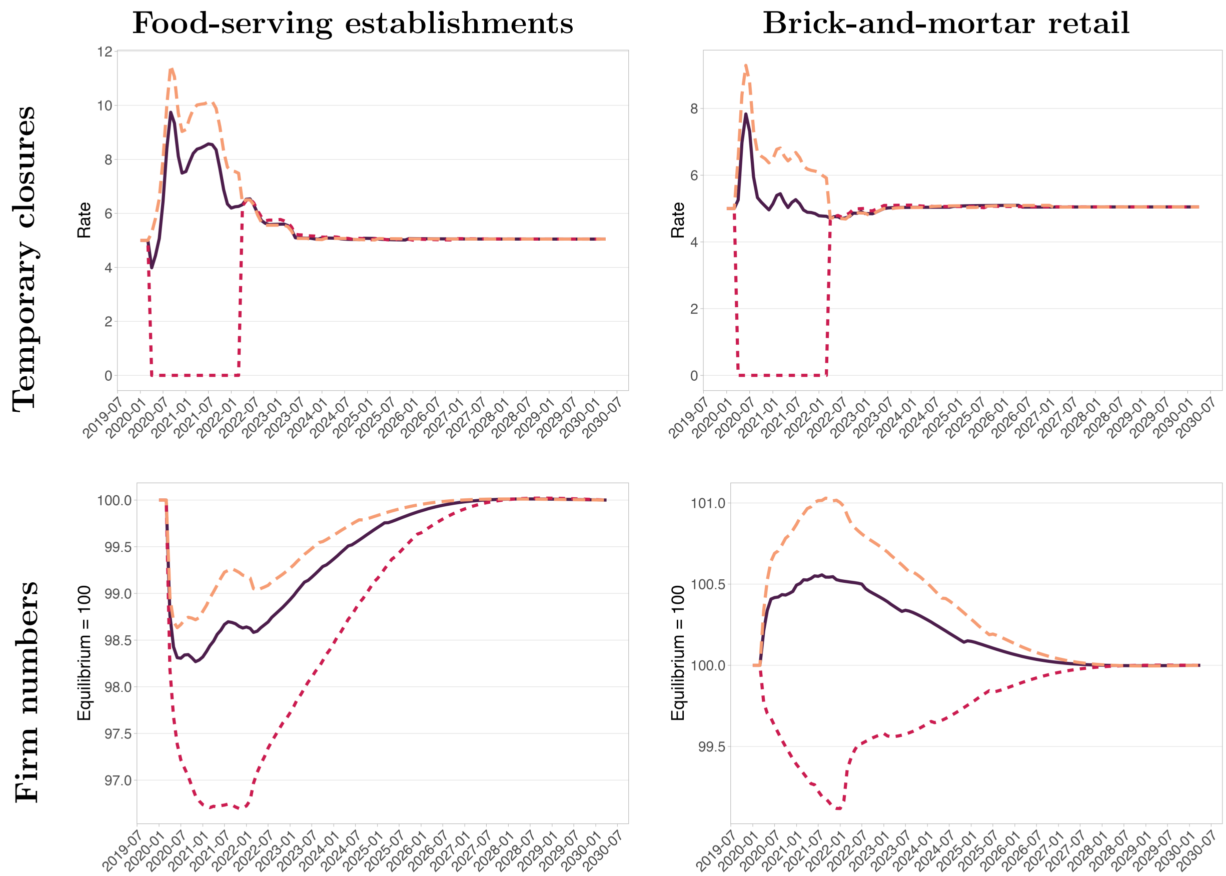
Figure 12 shows the consequences of temporary closures on prices and employment, expressed as the percentage differences of the two counterfactuals to the baseline scenario.[21] The plain cyan lines in the top panels show that, absent temporary closures, the price levels would have been larger during the reopening and post-pandemic phases in 2023. Prices would have been 0.52% higher than in the baseline in July 2024 in the food-service sector and 0.36% higher in the retail sector. Note, that our estimated price changes are, strictly speaking, Laspeyres price changes, as we do not allow for substitution effects on spending when prices change.[22]

The dashed line in the top panels shows that subsidising temporary closures by 10% more until January 2022 would have reduced the post-pandemic price level compared to the base-

[21] For completeness, Figure F.3 in Appendix F displays the percentage differences of the two counterfactuals to the baseline scenarios for the other firm dynamics variables.

[22] For instance, we assume that an increase in the prices restaurants charge would not lead to substitution and households shifting spending, for example, to home cooking. Given the large demand changes and the small additional price changes in our model, we do not expect spending shifts to have a large effect on our estimates.

Figure 11: Firm dynamics in the baseline and the counterfactuals



Note: The solid lines are the baseline scenarios with shares of the fixed costs that can be saved when temporarily shutting down $\tau = 0.275$. The short-dashed red lines show the counterfactuals where firms cannot exit temporarily $\tau = 0$. The long-dashed orange lines show the counterfactuals where firms save an additional 10% of their fixed costs when exiting production for the period ($\tau = 0.3025$). From February 2022 onwards, all firms can temporarily close and save the baseline share of their fixed costs, across all scenarios, to ensure convergence back to the steady state. Temporary closures are calculated as percentages of operational firms. Firm numbers are normalised to equal 100 in the steady state.

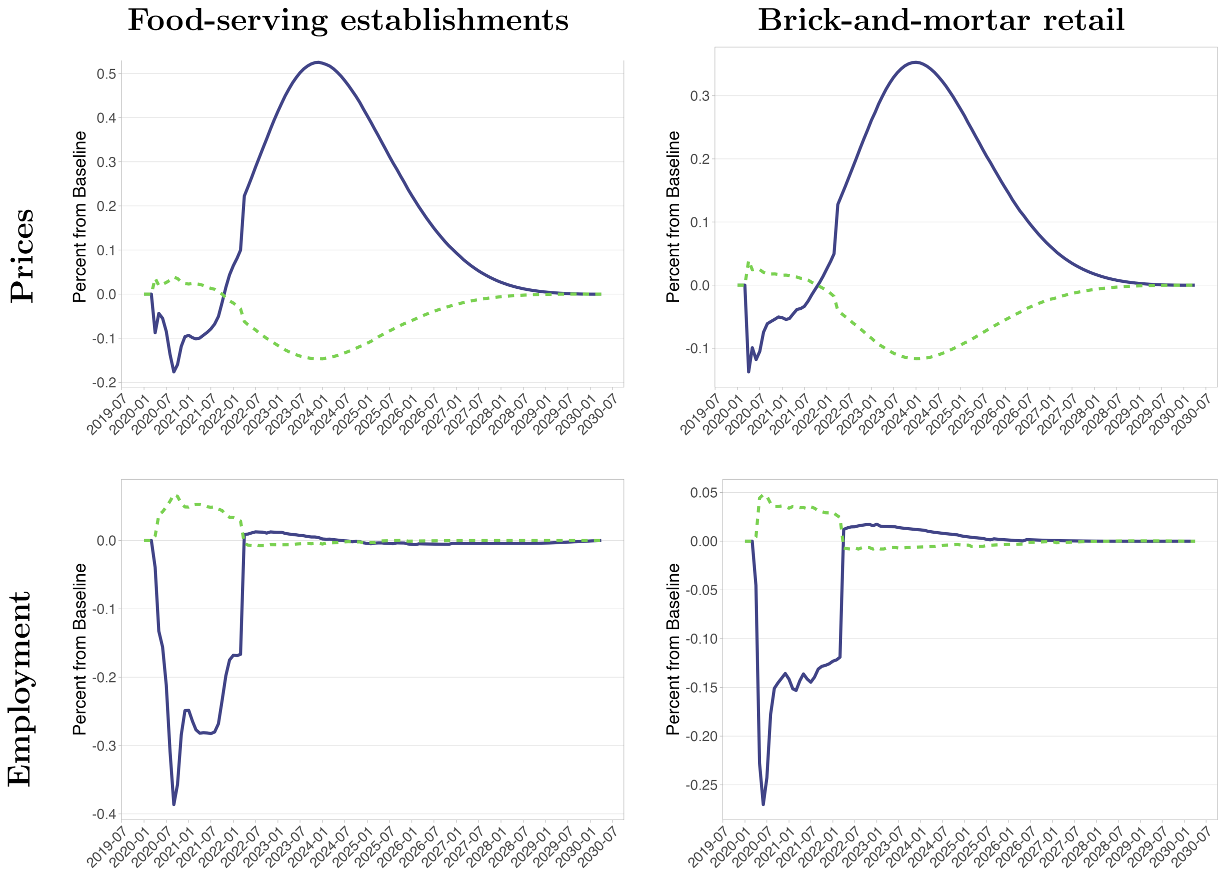
line. Intuitively, the reason is that temporary closures prevent frictional costs from firms exiting and re-entering the market. Thus, with stronger incentives for lower-productivity firms to temporarily close their production, those firms would have been ready to provide supply when demand in the economy recovered, limiting the supply bottlenecks that were observed during the reopening phase of the pandemic. Thus, the price level would have risen by less and fewer new entrants (that needed to pay a fixed cost of entry) would have been needed to bring production back to the steady state.

Our results suggest the existence of a new channel whereby temporary closures and government subsidies are designed to temporarily help struggling businesses prevent additional price pressures after a large demand shock like the pandemic. In our simulations, temporary closures prevent an additional 0.3% of equilibrium price increases in 2022 and 2023. Of course, our simple model of business dynamics does not include other channels that may be quantitatively relevant. We do not assess the overall impact of government spending during the pandemic, which may have put upward pressure on post-pandemic price increases and inflation. We merely state that targeted government spending supporting temporarily closed businesses (e.g., subsidized furlough programs) may have put *downward* pressure on post-pandemic inflation.

The bottom panel of Figure 12 shows the total employment, defined as total salary payments, by firms for the counterfactual scenarios relative to the baseline. The plain lines show that, in both sectors, employment would have fallen by more, relative to the baseline scenario, if temporary closure had not been an option for firms. The employment loss would have been stronger in the food-service than in the retail sector. Both sectors enjoy a brief period of increased employment during the recovery, driven by the labour effort necessary to establish new entrants. This is consistent with the labour shortage experienced during the recovery phase of the pandemic. The dashed line shows that, with further government subsidies increasing the share of temporarily closing firms, employment would have fallen less than in the baseline. This is non-obvious as a subsidised temporary closure would decrease a firm's salary payments. However, this within-firm wage-bill reduction is outweighed by more firms surviving and thereby providing more employment opportunities overall.

Our simulations, calibrated to the temporary-closure rates computed from Google Places, show that temporary closure meant more firms survived the observed consumption shock triggered by the COVID-19 pandemic in the food-service and retail sectors. This provided the economy with a higher supply capacity during the reopening phase of the pandemic. For the two sectors we consider, our counterfactual simulations show that temporary closures

Figure 12: Prices and employment in the counterfactuals relative to the baseline



Note: The solid line shows the percent change when firms cannot exit temporarily until January 2022, compared to the baseline. The dashed line shows the percent change when temporary closure is subsidised 10% more until January 2022, compared to the baseline. From February 2022 onwards, all firms can temporarily close and save their baseline share of the fixed costs, across all baseline and counterfactual scenarios, to ensure convergence back to the steady state. Employment is defined as the total salary payments.

resulted in lower unemployment during the pandemic, lower labour shortages in 2022 and 2023, and lower equilibrium prices in 2022 and 2023. Further subsidizing temporary closures by governments during the pandemic would have been associated with additional downward pressure on the price level.

6 Conclusion

In this paper, we highlight a possible channel whereby mothballed businesses can curb equilibrium prices in an industry after a severe demand shock. As a case study, we use the post-COVID-19 reopening of two industries: brick-and-mortar retail and food-serving establishments in urban areas in Canada.

We first present a new way to measure temporary closures, where we use Google Places to highlight the relevance of establishment-level metadata for small businesses. On one hand, the temporary-closure flag reflects the active operation of an establishment, something that is not captured well by the usual annual updates in administrative data. On the other hand, business reviews correlate with business dynamics and job vacancies, such that preventing well-rated businesses from permanently exiting could support employment.

We then proceed to develop a heterogeneous model of firm dynamics where firms differ in their productivity and activity states. We add the option for firms to temporarily close (that is, to save on their cost of operating) or to permanently exit, depending on their individual productivity state and expected demand. After a negative demand shock, some firms will only temporarily close, such that the economy saves on the cost of re-entry and retains more productive capacity, implying a reduction in price pressures. When applying our framework to the COVID-19 episode, we find that the "mothballing" of establishments helped preserve employment. Absent temporary closures, the food-service and the brick-and-mortar retail sectors would have faced more price pressures, respectively additional 26 and 18 basis point increases in the equilibrium price, per year, in 2022 and 2023. Eventually, our counterfactuals show that government subsidies for temporarily closed businesses likely contributed to this deflationary pressure.

Still, our work focuses on one specific channel and, thus, abstracts from other mechanisms, such that future research should consider introducing business reviews and temporary closures into larger-scale general-equilibrium models of firm dynamics.

References

Aghion, P., A. Bergeaud, T. Boppart, P. J. Klenow, and H. Li (2019): "Missing growth from creative destruction," *American Economic Review*, 109, 2795–2822.

Bahaj, S., S. Piton, and A. Savagar (2022): "Business creation during Covid-19," Bank of England working papers 981.

Bilbiie, F. O., F. Ghironi, and M. J. Melitz (2012): "Endogenous entry, product variety, and business cycles," *Journal of Political Economy*, 120, 304–345.

Boppart, T., P. Krusell, and K. Mitman (2018): "Exploiting MIT shocks in heterogeneous-agent economies: the impulse response as a numerical derivative," *Journal of Economic Dynamics and Control*, 89, 68–92.

Buera, F. J., R. N. Fattal-Jaef, H. Hopenhayn, P. A. Neumeyer, and Y. Shin (2021): "The economic ripple effects of COVID-19," Tech. rep., National Bureau of Economic Research.

Buera, F. J., R. N. F. Jaef, and Y. Shin (2015): "Anatomy of a credit crunch: from capital to labor markets," *Review of Economic Dynamics*, 18, 101–117.

Bustamante, C. (2020): "Debt Overhang, Monetary Policy, and Economic Recoveries After Large Recessions," Staff working papers.

Crane, L. D., R. A. Decker, A. Flaaen, A. Hamins-Puertolas, and C. Kurz (2022): "Business exit during the COVID-19 pandemic: Non-traditional measures in historical context," *Journal of Macroeconomics*, 72.

Decker, R. and J. Haltiwanger (2023): "Surging Business Formation in the Pandemic: Causes and Consequences?" *Brookings Papers on Economic Activity*, 3–24.

Dixit, A. (1989): "Entry and exit decisions under uncertainty," *Journal of political Economy*, 97, 620–638.

Dixit, A. K., R. S. Pindyck, and R. Pindyck (1994): "Investment under uncertainty," *Press, Princeton, New Jersey.*

Duguid, J., B. Kim, L. Relihan, and C. Wheat (2023): "The Impact of Work-from-Home on Brick-and-Mortar Retail Establishments: Evidence from Card Transactions," *Available at SSRN 4466607.*

Duprey, T., D. E. Rigobon, A. Kotlicki, and P. Schnattinger (2023): "Timely Business Dynamics Using Google Places," in *AEA Papers and Proceedings*, American Economic Association, vol. 113, 135–139.

Duprey, T., D. E. Rigobon, P. Schnattinger, A. Kotlicki, S. Baharian, and T. R. Hurd (2022): "Business closures and (re)openings in real-time using Google Places: proof of concept," *Journal of Risk and Financial Management.*

Gourinchas, P.-O., S. Kalemli-Özcan, V. Penciakova, and N. Sander (2021): "COVID-19 and small- and medium-sized enterprises: A 2021 "time bomb"?" *AEA Papers and Proceedings*, 111, 282–86.

Gourinchas, P.-O., ebnem Kalemli-zcan, V. Penciakova, and N. Sander (2023): "SME Failures Under Large Liquidity Shocks: An Application to the COVID-19 Crisis," Staff Working Papers 23-32, Bank of Canada.

Guerra, M., P. Kort, C. Nunes, and C. Oliveira (2018): "Hysteresis due to irreversible exit: Addressing the option to mothball," *Journal of Economic Dynamics and Control*, 92, 69–83.

Haltiwanger, J. C. (2021): "Entrepreneurship during the COVID-19 pandemic: Evidence from the Business Formation Statistics," Tech. Rep. 28912, National Bureau of Economic Research.

Hamano, M. and F. Zanetti (2017): "Endogenous product turnover and macroeconomic dynamics," *Review of Economic Dynamics*, 26, 263–279.

——— (2022): "Monetary policy, firm heterogeneity, and product variety," *European Economic Review*, 144, 104089.

Hopenhayn, H. and R. Rogerson (1993): "Job turnover and policy evaluation: A general equilibrium analysis," *Journal of Political Economy*, 101, 915–938.

Hopenhayn, H. A. (1992): "Entry, exit, and firm dynamics in long run equilibrium," *Econometrica: Journal of the Econometric Society*, 1127–1150.

Khan, A. and S. Lee (2023): "Persistent Debt and Business Cycles in an Economy with Production Heterogeneity," Staff Working Papers 23-17, Bank of Canada.

Kurmann, A., Étienne Lalé, and L. Ta (2021): "The Impact of COVID-19 on Small Business Dynamics and Employment: Real-Time Estimates with Homebase Data," CIRANO Working Papers 2021s-26.

Office for National Statistics (2022): "Business demography, quarterly experimental statistics, UK; July to September 2022," Report, ONS.

Peterman, W. B. (2016): "Reconciling micro and macro estimates of the Frisch labor supply elasticity," *Economic inquiry*, 54, 100–120.

Ravn, M. O. and H. Uhlig (2002): "On adjusting the Hodrick-Prescott filter for the frequency of observations," *Review of economics and statistics*, 84, 371–376.

Sedláček, P. (2020): "Lost generations of firms and aggregate labor market dynamics," *Journal of Monetary Economics*, 111, 16–31.

Statistics Canada (2020): "Experimental estimates for business openings and closures for Canada, provinces and territories, census metropolitan areas, seasonally adjusted," Table 33-10-0270-01, Statistics Canada.

——— (2021): "Real-time Local Business Conditions Index: Concepts, data sources, and methodology," Report, Statistics Canada.

Statistics Canada, C. N. S. O. (2020): "Quarterly estimates of business entry and exit," https://doi.org/10.25318/3310016501-ENG.

Tauchen, G. (1986): "Finite state markov-chain approximations to univariate and vector autoregressions," *Economics letters*, 20, 177–181.

Toast Inc. (2024a): "How Much Does It Cost to Open A Bar? (2024 Bar Startup Costs)," https://pos.toasttab.com/blog/on-the-line/how-much-does-it-cost-to-open-a-bar, (Accessed on 10/07/2024).

——— (2024b): "How Much Does It Cost to Open a Cafe? (2024 Cafe Startup Costs)," https://pos.toasttab.com/blog/on-the-line/how-much-does-it-cost-to-open-a-cafe#:~:text=%2480%2C000%20to%20%24300%2C000%20for%20a,a%20coffee%20stand%20or%20kiosk, (Accessed on 10/07/2024).

——— (2024c): "How Much Does it Cost to Open a Nightclub? (2024 Nightclub Startup Costs)," https://pos.toasttab.com/blog/on-the-line/how-much-does-it-cost-to-open-a-nightclub#:~:text=Average%20Cost%20of%20Opening%20a%20Nightclub&text=On%20average%2C%20opening%20a%20bar,Security%20and, (Accessed on 10/07/2024).

——— (2024d): "How Much Does it Cost to Open a Small Restaurant? (2024 Small Restaurant Startup Costs)," https://pos.toasttab.com/blog/on-the-line/how-much-does-it-cost-to-open-a-small-restaurant#:~:text=When%20looking%20at%20the%20average,%24175%2C000%20to%20well%20over%20%24700%2C000., (Accessed on 10/07/2024).

Yelp (2020): "Local Economic Impact Report," Tech. rep., Yelp.

Appendix for "Bouncing Back: How Mothballing Curbs Prices"

Thibaut Duprey Artur Kotlicki Daniel Rigobon Philip Schnattinger

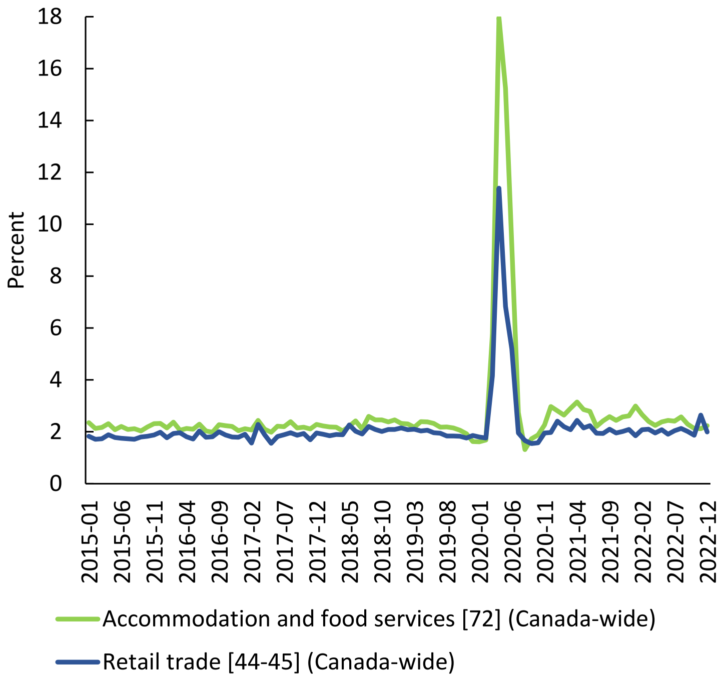
A Comparison with Statistics Canada estimates

The publicly available estimates of temporary closures produced by Statistics Canada in Figure A.1 do not have the granular breakdown we have in our sample and rely on a different definition of temporary closures. Because this Statistics Canada data relies on monthly payroll records from the Canada Revenue Agency, combined with the Business Register, the temporary-closure estimates reflect enterprise-level temporary closures and capture only temporary closures for businesses with at least one employee. To be classified as a temporarily closing business, a business must have had paid employment in the previous month but no paid employment in the given month. A business classified as a permanent exit would have had paid employment before but no paid employment in the given month and any of the subsequent periods. Instead, in our dataset derived from Google Places, we capture establishment-level closures for businesses, irrespective of the number of employees, and the temporary closures correspond to the actual establishment not being opened for business to the public, even if some employees remained on the payroll.

This difference in definitions likely explains the significant difference in the magnitude of our estimates of temporary closures. From the Statistics Canada data in Figure A.1 we observe that the temporary-closure rate spiked at 18.0 and 11.4% around the first lockdown in March 2020, respectively for the accommodation, food-service, and the retail trade sectors. This is an increase by between 16.3 and 9.6 percentage points, compared to an increase by 0.4 and 0.2 percentage points during the second lockdown in April 2021, respectively, for each sector. Alternatively with our estimates in Figure 2b, although we did not collect data on the first lockdown, we observe a large increase in temporary-closure rates during the second lockdown in April 2021. Our temporary-closure rates peak at 11 and 7%, respectively, for each sector, compared to a long-term trend of 5% for both sectors.

B Scraping algorithm

Figure A.1: Temporary closures with the experimental estimates from Statistics Canada



Note: Ratio of temporary closures in a given month compared to the number of active businesses from the previous month, Canada-wide estimates. Source: Statistics Canada experimental estimates for business openings and closures (Table: 33-10-0270-01).

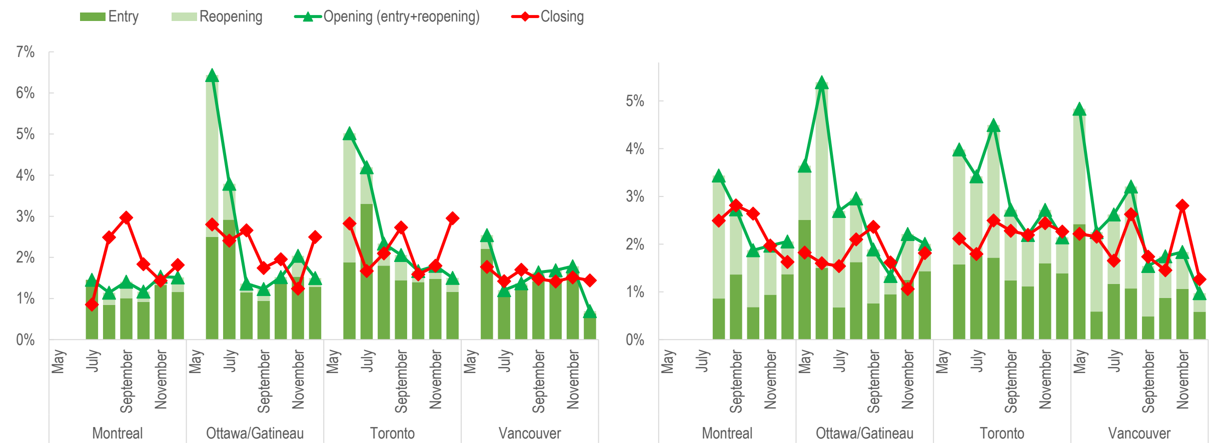
Algorithm 1 Algorithm to collect data from Google Places

Precondition: A is a two-dimensional polygon in latitude-longitude coordinates. df is globally initialized to be a (initially empty) DataFrame of query results.

function $\textsc{Scrape}(A)$
    Compute $B((x,y),r)$ to be the smallest circle containing area A centered over the coordinates (x,y) with a radius r
    $results,\ flag \leftarrow \textsc{Query}(B((x,y),r))$
    if $flag$ **then**
        Compute $A_1, \ldots, A_4 = B((x \pm \frac{r}{2}, y \pm \frac{r}{2}), \frac{r}{2})$
        for $i = 1, \ldots, 4$ **do**
            Add $\textsc{Scrape}(A_i)$ to df
        end for
    else
        Add $results$ to df
    end if
    return df
end function

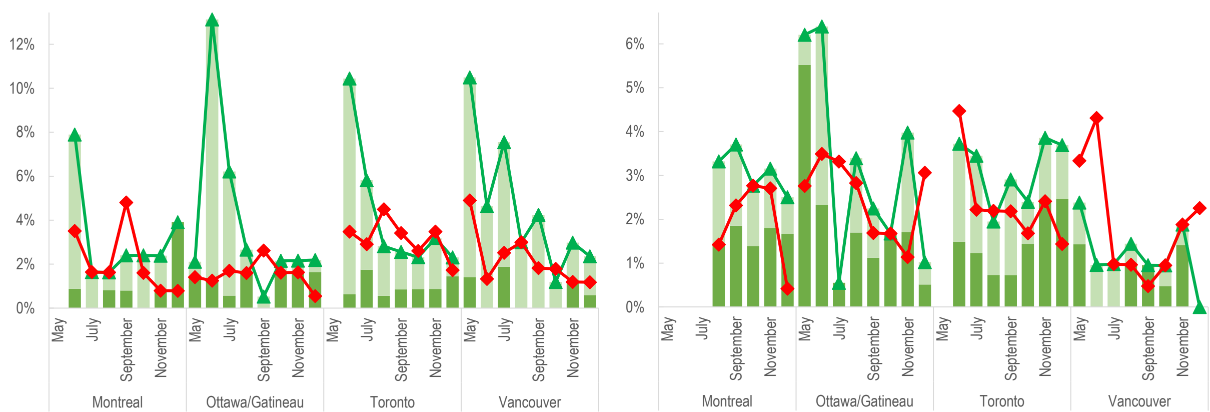
C Graphical appendix

Figure C.1: Phased reopenings, after the April 2021 lockdowns, across sectors and cities



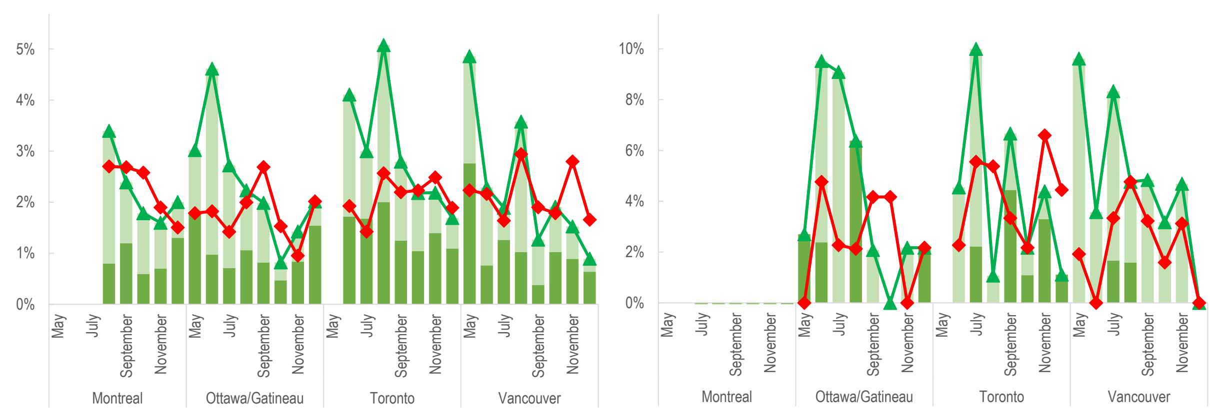
(a) Retail sector, NAICS 44-45

(b) Food-service sector, NAICS 722



(c) Bar

(d) Cafe



(e) Restaurant

(f) Night club

Note: The figure displays the monthly opening and closure rates for downtown Toronto, Vancouver, and Ottawa/Gatineau, derived from Google Places data, split by sectors and keywords. The food-service sector is the aggregation of the results by the keywords **bar**, **cafe**, **restaurant**, and **night_club**. In April, we did not collect data for the retail sector across cities nor for the food-service sector for Toronto, so the opening and closure rates are not computed for May. For Montreal (Quebec), systematic data collection started only after the reopening phase of the pandemic and too few observations are available for night clubs.

D Timeline of changes in COVID-19 restrictions

Month	British Columbia	Ontario
April		Apr 3. Four-week lockdown for the entire province Apr 8. Stay-at-home order for the entire province
May	May 25. Phase 1 reopening: Indoor and outdoor dining with capacity limits	
June	Jun 15. Phase 2 reopening: Maximum of 50 people for outdoor social gatherings and 50 people for seated indoor organized gatherings	Jun 2. Ontario's stay-at-home order expired on Jun 11. Step 1 of reopening: Outdoor dining with up to four people per table, non-essential retail at 15% capacity, essential retail at 25% capacity; retail stores in malls remain closed unless they have a street-facing entrance Jun 30. Step 2 of reopening: Outdoor dining with up to six people per table, non-essential retail at 25% capacity, essential retail at 50% capacity
July	Jul 1. Phase 3 reopening: Night clubs reopen with capacity limits; return to normal hours for liquor service at restaurants and bars	Jul 16. Step 3 of reopening: Indoor dining with no limits per table, essential and non-essential retail with capacity limited to the number of people that can maintain physical distancing, night clubs at up to 25% capacity or up to 250 people
August		
September		Sept 24. Capacity limits eased for settings where proof of vaccination is required

Note: The metropolitan area of Ottawa/Gatineau is divided by a river, with the city of Ottawa on one side (Ontario) and the city of Gatineau on the other side (Quebec), such that the two sides had different sets of restrictions. However, Gatineau accounts for fewer observations of the Ottawa/Gatineau area, and the area around Gatineau followed a similar timing to Ontario, with a lockdown in April and the start of the reopening from May 31 onward and then throughout June.

Table D.1: Phased reopenings across provinces for retail and food-service sectors in 2021

E Residualizing change in reviews

Variable	Coefficient	Standard Error
Sector=Food service	3.31***	(0.61)
Sector=Retail	-8.09***	(0.58)
Sector=Accommodation	5.76***	(0.82)
City=Vancouver	-0.25	(0.73)
City=Montreal	10.92***	(0.72)
City=Toronto	7.00***	(0.63)
Date=May. 2021	197.78***	(1.37)
Date=Jun. 2021	14.40***	(1.32)
Date=Jul. 2021	1.17	(1.26)
Date=Aug. 2021	2.96**	(1.27)
Date=Sep. 2021	1.94	(1.27)
Date=Oct. 2021	1.59	(1.27)
Date=Nov. 2021	1.68	(1.27)
Date=Dec. 2021	0.35	(1.27)
Date=Jan. 2022	-0.42	(1.27)
Date=Feb. 2022	3.71***	(1.27)
Date=Mar. 2022	1.66	(1.26)
Date=Apr. 2022	0.86	(1.26)
Date=May, 2022	1.13	(1.26)
Date=Jun. 2022	2.72**	(1.26)
Date=Jul. 2022	2.60**	(1.26)
Date=Aug. 2022	5.53***	(1.26)
Date=Sep. 2022	2.90**	(1.26)
Date=Oct. 2022	0.97	(1.26)
Date=Nov. 2022	1.88	(1.26)
Date=Dec. 2022	1.14	(1.26)
R-squared	0.1163	
R-squared Adj.	0.1162	

Note: Coefficients from the estimation of Equation (1) used to residualize individual establishments' change in reviews. The constant term and the dummy variable "City=Ottowa/Gatineau" are not included, to avoid collinearity with temporal fixed effects. Standard errors are in parentheses. Significance is denoted by: $*p < .1$, $**p < .05$, $***p < .01$.

Table E.1: Regression to residualize establishments' change in reviews

F Model appendix

F.1 Calibration of the wage elasticity to changes in demand

To close the labour market section of our model, we estimate the reaction of the real hourly wage to changes in labour demand. Our estimation here is purposely kept simple. We calculate the real hourly wage in each sector by deflating the hourly wages (Statistics Canada, Table 14-10-0326-01) using the CPI (Statistics Canada, Table 18-10-0006-01). We control for the detrended sectoral unemployment rate to capture variations in the labor supply in a sector. Finally, we use the lag of the employment deviations from the trend to instrument for the effects of a variation in employment on the wage. While the results are similar using OLS, we instrument with a lag to avoid changes in today's wage affecting employment demand. Our estimation period focuses on January 1997 (February 1997 with the instrument) to December 2019: we exclude the COVID period with large government interventions in the labour market that may otherwise influence our elasticity.

Table F.1 presents estimates of the reaction of wages to variations in labour input for the retail and food-service sectors. These estimates are comparable to conventional calibrations of the Frisch elasticity of labour supply to variations in labour demand affecting the wage (Peterman, 2016), which are typically around 2 for aggregates, meaning an equilibrium change of the wage to a labour input of about 0.5. Models (1) and (2) estimate a simple OLS for the food-service and retail sectors. Models (3) and (4) use an IV regression replacing employment deviations with their lag from three months ago for the food-service, accommodation, and retail and wholesale trade sectors. Our preferred specifications are Columns (3) and (4), which we use to calibrate the parameter ζ of the wage reaction to variations in employment demand.

F.2 Computational details

To compute the transitions of idiosyncratic firm productivity, we discretize the firm state space over a grid of 2,000 points. The points and the transition matrices for these points are provided by the Tauchen (1986) method for discretizing an AR(1) process.

We solve the model for each sector separately, taking demand as given from the observed data. Wages and prices adjust endogenously to clear the goods and labour markets. First, we solve for the steady state of the model with temporary closures. Then we simulate an MIT shock, where the demand path follows the observed demand from January 2020 until May 2023. From that point on, we assume that the demand path is constant at 100 (the pre-

Dependent variable:	Real hourly wage			
Model:	(1)	(2)	(3)	(4)
Constant	0.0002	0.0002	0.0007	0.0006
	(0.0017)	(0.0015)	(0.0017)	(0.0014)
Unemployment rate (PctDevHPtrend)	0.0743***	0.0954***	0.0811***	0.0840***
	(0.0186)	(0.0177)	(0.0193)	(0.0165)
Employed (PctDevHPtrend)	0.3112***	0.6136***	0.3479***	0.4667***
	(0.0889)	(0.1762)	(0.0929)	(0.1565)
Observations	240	240	264	264
R^2	0.06537	0.10934	0.06666	0.09040
Adjusted R^2	0.05748	0.10183	0.05951	0.08342

Note: All data is presented in deviations from a Hodrick Prescott trend (*PctDevHPtrend*), using the monthly detrending parameters suggested by Ravn and Uhlig (2002). Data used is the real median wage deflated with the CPI index, the sectoral unemployment rate, and employment numbers. IID standard errors are in parentheses. Models (1) and (3) estimate the relations for the food-service sector with OLS and IV and models (2) and (4) estimate the relations for the retail sector. Significance is denoted by: *$p < .1$, **$p < .05$, ***$p < .01$.

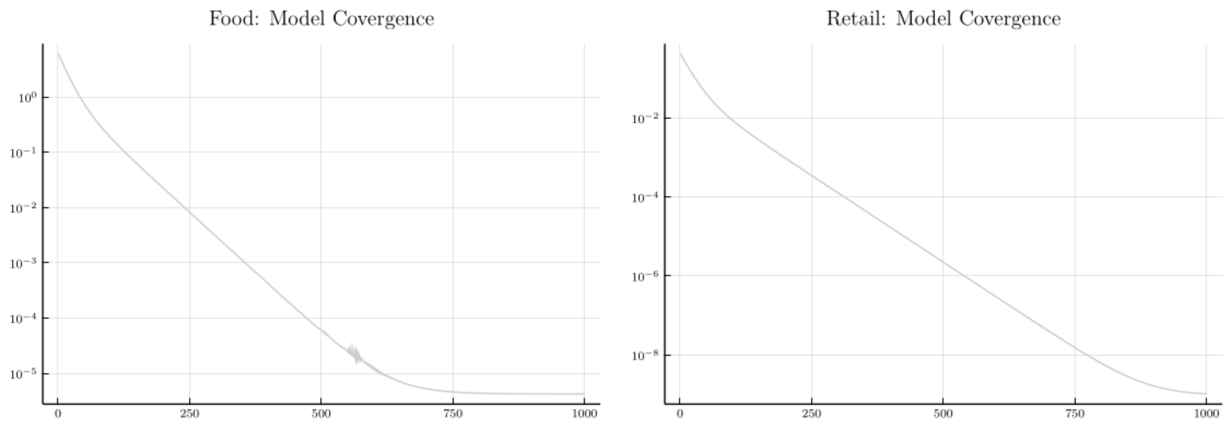
Table F.1: Estimates of changes in employment to the real wage

pandemic normalized level after detrending) until January 2042, where we assume the model converged back to the steady state and, thus, approximately 20 years after the pandemic.

We solve the model in the following way. Supply, Y, is determined by the number and distribution of firms in the market, over time. We solve for the supply of firms by solving for the equilibrium path of optimal entry, the permanent-exit and temporary-closure choices of firms, given a guessed price, p^0, and a guessed wage path, w^0. Given the entry and exit choices, we then compute firm output, firm numbers, and aggregate supply, Y^0, and aggregate labour demand, L^0. From aggregate supply and labour demand, we can calculate updated price and wage levels, $p^0_{updated}$ and $w^0_{updated}$, using Equation (10), and the exogenous path for aggregate demand. We then update the next period's guess for the price and wage levels, in small steps, $p^1 = (1-\lambda)p^0 + \lambda p^0_{updated}$ and $w^1 = (1-\lambda)w^0 + \lambda w^0_{updated}$, with $\lambda = 0.01$. We iterate until the updated steps become small enough, that is, until we have reached a dynamic equilibrium path.

The model converges quickly to the equilibrium price path, and after 300 iterations, no meaningful difference between the price path updates p^{299} and p^{300} can be detected. In this case, the summed Euclidian differences in the price vector are below 10^{-6} as shown in Figure F.1.

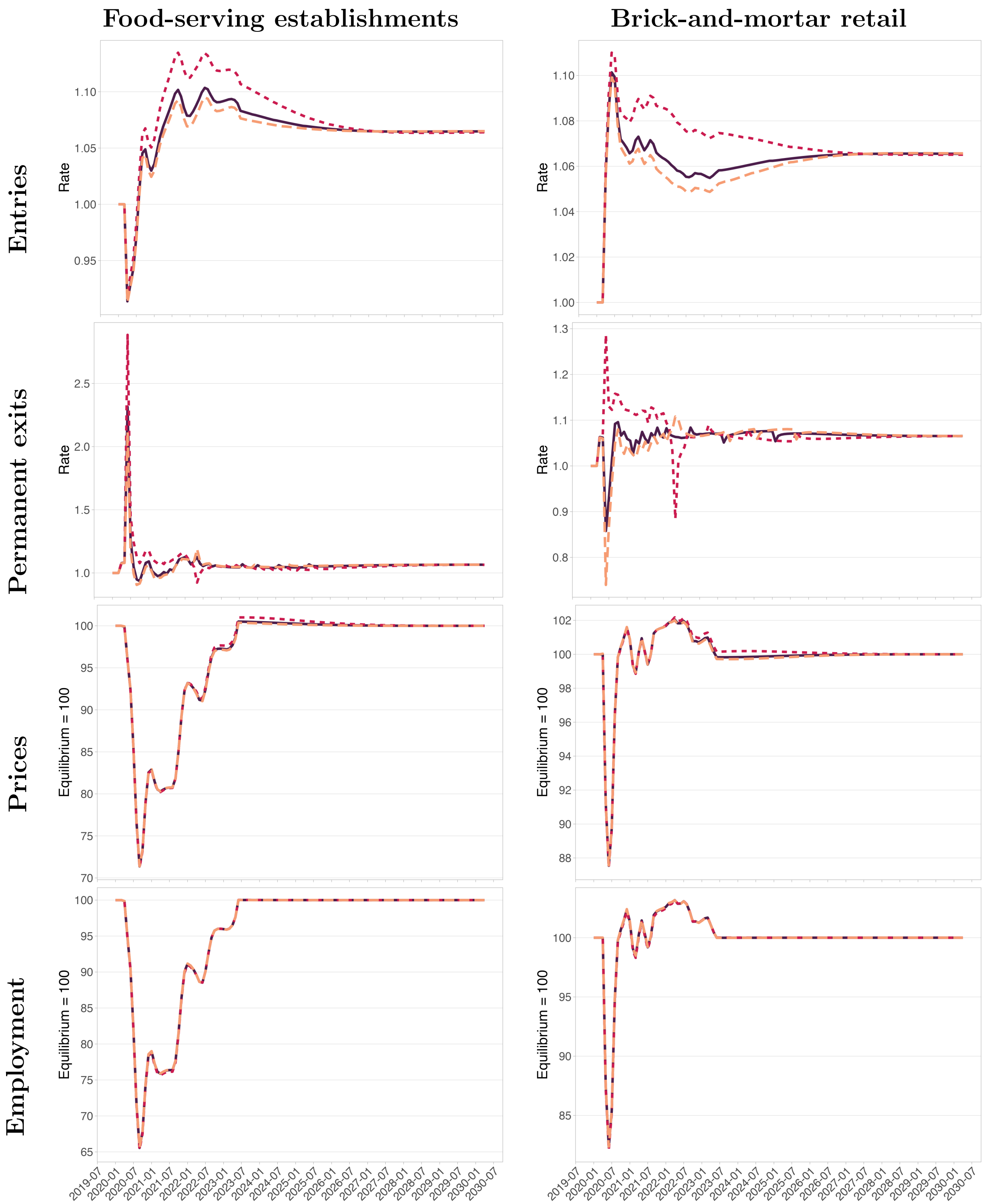
Figure F.1: Convergence of the price path to equilibrium as the Euclidian distance between the price-path updates $(p^x - p^{x+1})^2$ shrinks



F.3 Additional model output

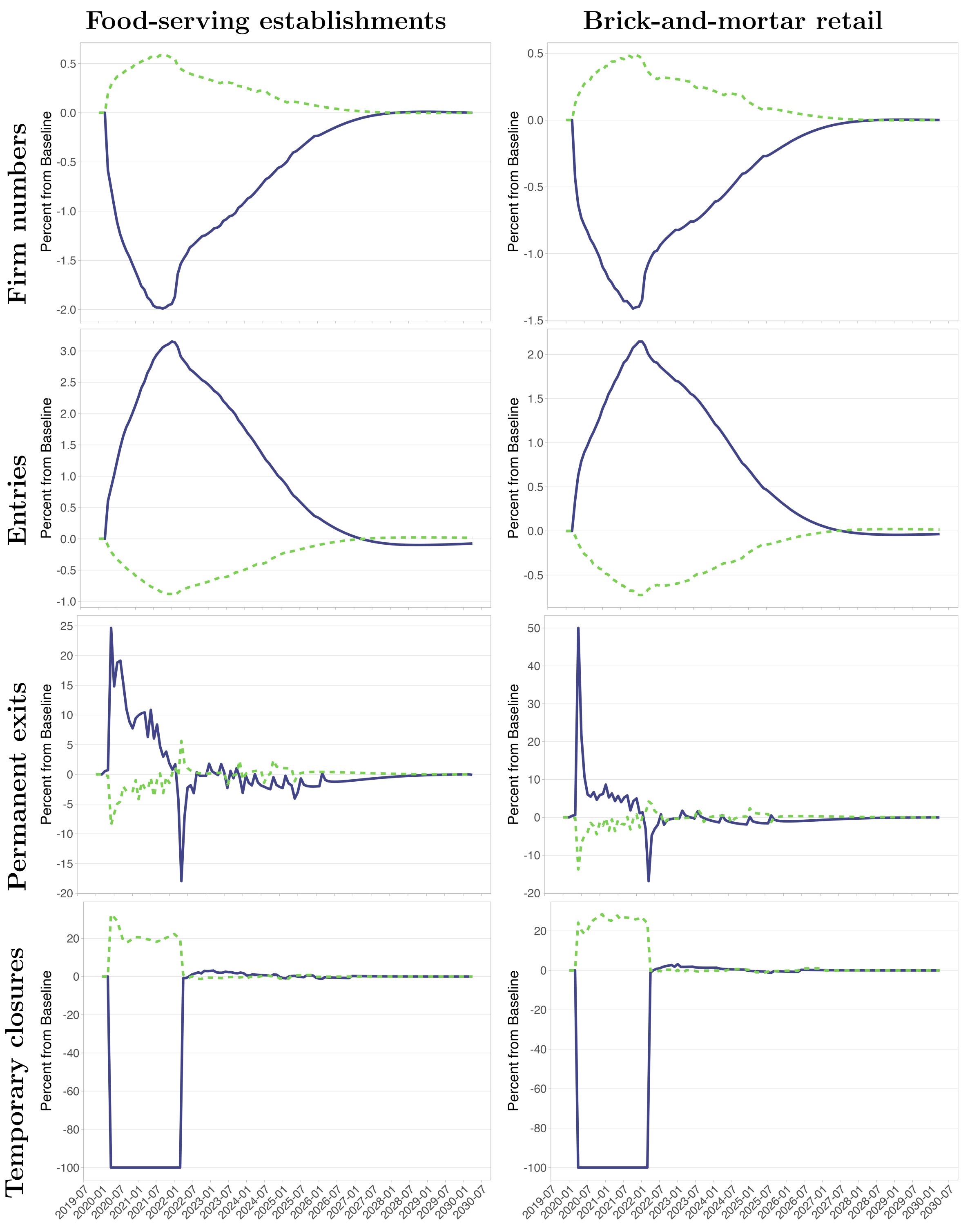
We provide the output related to model simulations in the baseline and the counterfactuals in Figure F.2, and to firm dynamics in the counterfactuals relative to the baseline in Figure F.3.

Figure F.2: Model simulations in the baseline and the counterfactuals



Note: The solid line is the baseline scenario with a share of fixed costs that can be saved when temporarily shutting down, $\tau = 0.275$. The short dashed red lines show the counterfactuals where firms cannot exit temporarily $\tau = 0$. The long dashed orange lines show the counterfactuals where firms save an additional 10% of the fixed costs when exiting production for the period ($\tau = 0.3025$). From February 2022 onwards, all firms can temporarily close and save their baseline share of fixed costs, across all scenarios, to ensure convergence back to the steady state. Entries and permanent exits are calculated as percentages of operational firms. Prices and employment are normalised to equal 100 in the steady state. Employment is defined as the total salary payments.

Figure F.3: Firm dynamics in the counterfactuals relative to the baseline



Note: The solid line shows the percent change when firms cannot exit temporarily until January 2022 compared to the baseline. The dashed line shows the percent change when temporary closure is subsidised 10% more until January 2022 compared to the baseline. From February 2022 onwards, all firms can temporarily close and save their share of the baseline fixed costs across all baselines and counterfactual scenarios, to ensure convergence back to the steady state.